Dimension Reduction Approaches for Psycholexical Investigations

by

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DISSERTATION ABSTRACT

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Some of the most prominent structures of personality have been derived from the psycholexical tradition (e.g., the Big Five). In this theory, natural language has encoded a structure of personality that can be assessed by analyzing relationships among words through means of dimension reduction. Much of the discourse around subsequent findings has centered on which terms or populations were sampled, neglecting the analyses employed. However, other fields have developed alternative dimension reduction methods appropriate for such work, only some of which have been embraced by psychologists and fewer still for psycholexical research. In Study 1, I compare the performance of common dimension detection algorithms on data simulated to resemble those derived from psychological surveys. Study 2 considers the performance of these algorithms on data simulated for a psycholexical study of personality, then applies the optimal approaches to a canonical dataset of personality structure. Study 3 further extends Study 2 by adding additional parameters to the generative process to improve their verisimilitude, then applies those findings to a different dataset of trait ratings. I demonstrate that the assumptions underlying the generative process in a psycholexical investigation can substantially shift both the optimal analytic approach and the structure identified. These findings highlight that the importance of establishing statistical validity has been underappreciated in the psycholexical tradition.

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Chapter 1: Introduction

The field of personality psychology is a diverse, active, and useful area of study. The mission of personality science is to provide a holistic framework for understanding a person (McAdams & Pals, 2006). A prominent area of personality research is in personality *structure*, which aims to provide patterns in inter-individual behavior, though other field including personality development (the trajectory of personality over the lifespan) and personality processes (explaining variable behavior in individuals) are common areas of study (Baumert et al., 2017).

Personality (the thoughts, emotions, and behaviors characteristic of an individual) is vast—one organizational theory of personality conceptualizes personality as a multi-leveled entity in which personality is expressed through dispositional *traits* (broad dimensions of personality), characteristic adaptations (contextualized motivational, social-cognitive, and developmental adaptions), and narrative identity (integrative life stories constructed to give meaning and identity), each of which differentially interacts with culture (McAdams & Pals, 2006). Structures based on relationships between traits have formed the basis for personality measurement.

Recent meta-analyses and reviews using trait-based measurement have demonstrated personality to be predictive of life outcomes, with effect sizes on par with those across other psychological disciplines (Roberts et al., 2007; Soto, 2019). These studies typically use structures of personality that implement broad constructs to summarize the wide breadth of elements that comprise personality.

Traits can be broad or narrow (Baumert et al., 2017). More specific (narrower) personality domains show stronger effects for relevant life outcomes at the expense of being more limited in scope (Mõttus et al., 2017; Vainik et al., 2015). Structures that incorporate both broad and narrow traits are therefore useful, as they allow the researcher to identify the scope of the personality domain in question. There is a tension introduced by the need to parsimoniously describe the inherently wide domain of personality that necessitates a rigorously specified structure. There has been much discussion about what form such a structure would take, with disagreements ranging across various levels of trait granularity (Ashton & Lee, 2007; Condon et al., 2020; Cramer et al., 2012; De Raad et al., 1992; Goldberg, 1990; Wiggins & Pincus, 1992).

The lengthy discourse around this debate is due to the import of a structure of personality. A rigorous structure of personality would allow further investigation and linkage to other constructs, whereas an exhaustive but poorly organized structure of personality would be limited by its scale. For example, if a person is modelled as a system including a million traits, that model would be of limited practical use (Condon et al., 2020). Conversely, some traits may be too broad to be particularly relevant to a given research question. This is the bandwidth-utility tradeoff. Therefore, the field of personality psychology has placed a high value on identifying a bounded set of personality components and a parsimonious description of their interrelationships, most notably resulting in Big Few trait models.

The primary such structure of personality is the Big Five (Goldberg, 1993), which characterizes personality as having five broad domains: Openness, Conscientiousness, Extraversion, Agreeableness, and Neuroticism. In this framework, Openness represents the dimension of personality of intellectual curiosity, aesthetic appreciation, and imaginative engagement with novel ideas and experiences. Conscientiousness encompasses the behavioral tendencies associated with self-discipline, organization, and goal-directed persistence. Extraversion—perhaps better termed "Surgency", considering the colloquial understanding of extraversion to mean sociability—represents individual differences in social engagement, assertiveness, and positive emotionality. Agreeableness captures individual differences in interpersonal orientation, specifically the tendency toward cooperative, trusting, and altruistic behavior versus competitive, skeptical, and self-interested approaches to social interaction. Neuroticism is characterized by emotional reactivity, stress vulnerability, and psychological adjustment (O. P. John et al., 1999).

The Big Five is likely the most popular structure of personality among laypersons and psychologists alike, with the possible exception of the Myers-Briggs Type Indicator among the former (Myers, 1962). A consensus on the Big Five as a model of personality among psychologists has largely been reached over the past thirty-some years.

One main paradigm has been employed in the development of the Big Five structure: the lexical hypothesis. This postulate states that fundamental individual differences (particularly in human interactions) will be encoded as single terms in a language (Galton, 1884). This implies a comprehensive—if not exhaustive—set of personality terms that can be easily queried through a dictionary. Furthermore, if those terms could be grouped according to their behavioral expression, those groups would yield a lower-dimensional representation of personality.

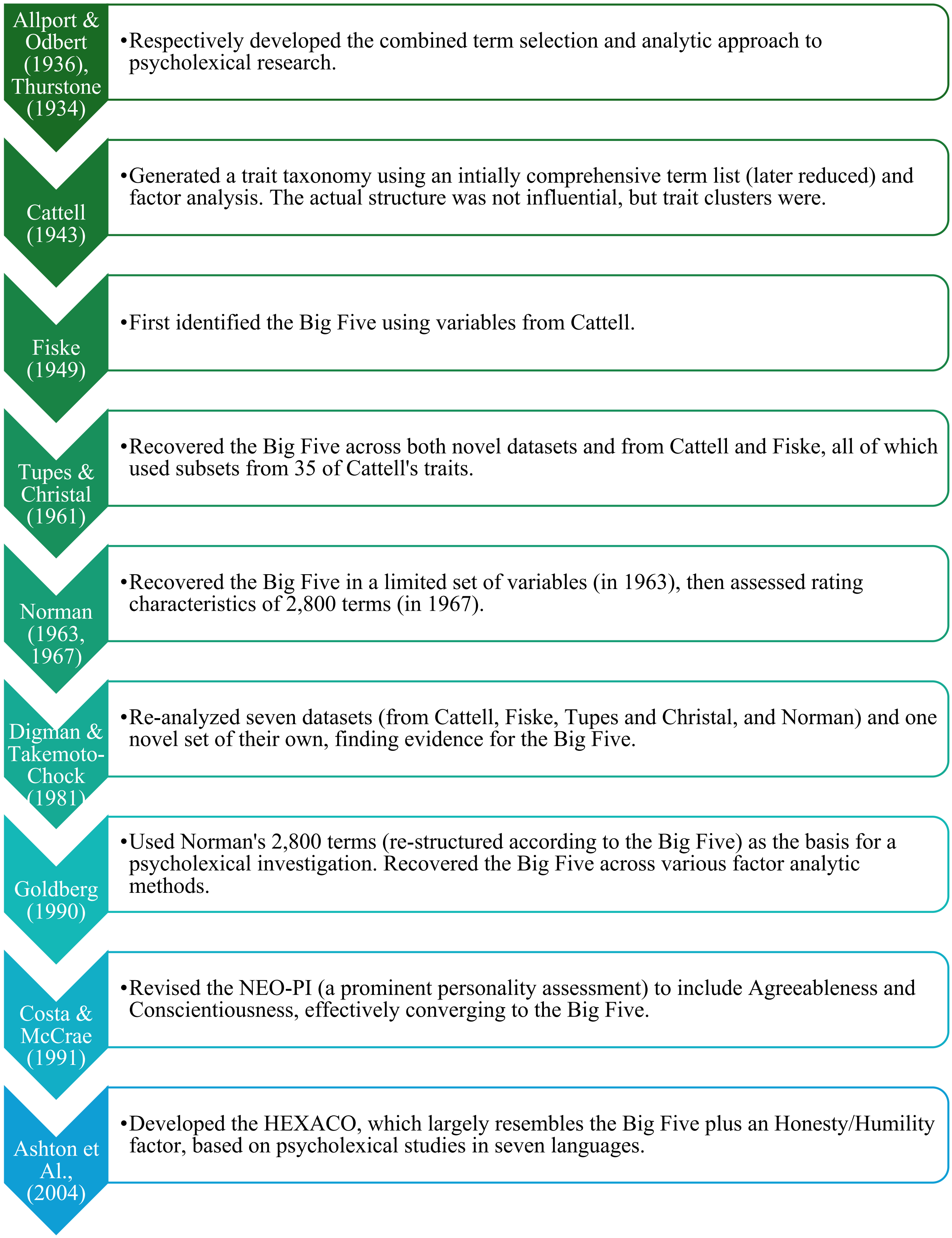
The approach to testing the lexical postulate, broadly speaking, is to identify a model that explains covariance among personality descriptors (often called trait descriptors or trait-descriptive adjectives for the case of adjectives). This has essentially been done in three steps: identifying a list of trait descriptors, querying the relationships among these trait descriptors, and reducing the dimensionality of these relationships (explain the relationships of many variables with fewer).

Each of these steps in the psycholexical tradition is fraught with difficulties. This work details many of those difficulties but substantively engages with the last step of dimensionality reduction. Past works in the lexical tradition have largely assumed that dimensionality reduction is constrained in the methods available to it and that conclusions from those constrained methods are empirically sound. This dissertation aims to first test those assumptions, then, second, generalize those findings beyond methods surrounding the lexical postulate. In the following sections, I first describe chronologically the development of the field of personality structure and primary findings in this field. Then, I outline the contemporary criticisms of these studies, focusing primarily on the methodological shortcomings; these shortcomings motivate the current dissertation.

History of the Lexical Approach

The foundation for testing the lexical approach is best attributed jointly to Allport and Odbert (1936) for their term selection, and Thurstone (1934) for the analytic approach (factor analysis) applied to selected terms. A more formal treatment of factor analysis follows, but essentially a factor is conceptualized as a statistical construct that explains patterns of relationships between variables. A timeline summarizing the events leading to the most prominent assessments in personality is below, with a more detailed textual recounting following. Although a rigorous genealogy of Big Few models would be a research portfolio unto itself, the major developments should be captured. It can be seen from this brief history that much of the work in the lexical tradition either did not use a large—much less comprehensive—set of terms or was pre-structured in accordance with the Big Five. The samples were also relatively homogeneous, being largely comprised of convenience samples of undergraduates.

Figure 1. A Timeline of Big Few Models



Allport and Odbert (1936), dredged through the second edition of Webster's Unabridged Dictionary to yield a list of almost 18,000 words that could be considered trait descriptors. These terms were organized into four categories (though it was noted that categories were not mutually exclusive): "neutral terms designating possible personal traits" (containing 4,504 terms), "terms primarily descriptive of temporary moods or activities", "weighted terms conveying social and characterial judgements of personal conduct or designated influence on others", and "metaphorical and doubtful terms." Those 4,504 neutral trait terms have since been the cornerstone for English language lexical investigations.

Thurstone (1934) developed the methods for a lexical investigation which would become the standard decades later. In this work, 1,300 participants provided ratings of 60 adjectives describing a target. Those ratings were then correlated and factored to identify five underlying factors—certainly not a comprehensive set of terms, but an impressive undertaking nonetheless as all calculations were done manually. As will be shown in this section, the underlying approach to developing a structure of personality has not strongly deviated from the joint approach of these two early works.

Cattell (1943) used the 4,504 category one terms from Allport & Odbert in addition to his own selection of 100 temporary-state terms. Through an iterative factoring process, he identified 35 trait variables. The correlations among these variables were factored to identify at least 12 factors of personality. These findings have not survived replication (Fiske, 1949; Norman, 1963; E. C. Tupes & Christal, 1958), but his 35-variable set was nonetheless influential, serving as the term selection for future lexical investigations (Block, 1995).

The earliest recognition of the Big Five belongs with Fiske (1949), who, in analyzing a set of 22 variables developed by Cattell, produced a set of five factors that closely resembles today's Big Five, though he did not follow up on these findings (L. R. Goldberg, 1993). Again, this set of 22 variables cannot reasonably be considered comprehensive as outlined by the lexical postulate.

In their groundbreaking Air Force technical report, Tupes and Christal (1961) analyzed sets of variables from Cattell and Fiske, as well as their own studies of Air Force officers, finding five recurrent factors derived from 35 personality traits, which they labelled as Surgency, Agreeableness, Dependability, Emotional Stability, and Culture. It should be noted to the reader that despite the different labels, these traits substantively mirror the same traits of the Big Five (Extraversion, Agreeableness, Conscientiousness, Neuroticism, and Openness). However, this factor structure is arguably a result of selecting a limited number of terms that were pre-structured into synonymous clusters; therefore, recovering these five factors is neither surprising nor of great personological insight (Block, 1995).

Norman (1963) replicated the five-factor model by factoring ratings from undergraduates on traits meant to represent the Big Five. Based on these findings, he attempted to develop an exhaustive taxonomy of personality descriptive terms (Norman, 1967). To that end, he retrieved 18,125 personality descriptive terms, excluding the vast majority of these terms on the basis that they were evaluative, anatomical/physical, ambiguous, or obscure/difficult. Thus, he yielded approximately 8,000 terms – 2,800 of which were deemed to represent stable biophysical traits. He administered lists of 200 terms each to undergraduate students, who were instructed to write down a synonym or definition of that word or cross it out if they did not know it. They then judged the extent to which that word described themselves, a liked peer, a neutral peer, and a disliked peer. Then they rated each word in terms of the social desirability of the word (O. P. John et al., 1988; Norman, 1967). Results of these analyses suggested excluding approximately

1200 words on the basis that they were too difficult, slangy, or extreme in self-ratings (O. P. John et al., 1988). The remaining 1,600 terms were sorted according to the Big Five dimensions, with broad classes representing each of the two poles per dimension. He further sorted these 10 classes into 75 semantic categories, and further sorted those categories into synonym clusters, yielding a hierarchical taxonomy of 571 synonym sets, 75 middle-level categories, and 10 superordinate classes. Importantly, these 75 semantic categories were rationally sorted according to a top-down implementation of the Big Five (Block, 1995).

Digman and Takemoto-Chock (1981) re-analyzed classic studies, including Cattell (1947), Fiske (1949), and Tupes & Christal (1961), along with their own data collection. Their findings, that the Big Five factors can be recovered across datasets, have been held by some as validating the Big Five. However, they found a variety of other factors as well, even in small sets of term ratings. Furthermore, the novel data set included was based on Cattell's variables.

In perhaps the most crucial study propounding the Big Five, Goldberg (1990) selected a subset of Norman's 2,800 trait descriptors to a more easily understood (by his sample of undergraduates) 1,710 terms (L. R. Goldberg, 1982). Those students provided ratings to those terms. The terms were aggregated to the 75 pre-structured scales by Norman, then subjected to a variety of factoring extraction (principal components, principal factors, alpha factoring, image factoring, and maximum likelihood procedures) and rotation (varimax and oblimin) methods. He compared the results across methods, finding a high degree of inter-method congruence and robustness of the Big Five structure. He recovered this structure in a set of 479 commonly used terms, selected also for their status as core traits of their respective factor in the Big Five (L. R. Goldberg, 1990). The assessment of structural robustness to analytic method was groundbreaking, though through the luxury of hindsight and advances in computer science, the choice of analyses appears constrained.

The NEO (Costa & McCrae, 1978) was originally designed to capture Extraversion and Neuroticism (consistent with Eysenck's prominent two-factor model; McCrae, 2008). This model was not based on the lexical tradition, but clinical research (McCrae & Costa, 1987). An additional Openness factor was later added, informed by the works of Tellegen & Atkinson (1974), Coan (1972), and prior work performed by the NEO's authors (Costa & McCrae, 1980). Costa and McCrae eventually were convinced to include Agreeableness and Neuroticism in the revised version of the NEO—the NEO-PI-R (Costa Jr & McCrae, 2008; Costa et al., 1991). Their markers for those added factors were derived from Goldberg, who had been presenting his findings at conferences prior to his major publications in the field (L. Goldberg, 1983). Subsequent discussion of the evolution of the NEO (and the Big Five more generally) has suggested that some key decisions were rooted in the desire for consensus as much as empirical evidence (see Goldberg, 1993 and Saucier & Iurino, 2020).

The Big Five Inventory (O. P. John et al., 1991) is another prominent personality measure that has its basis in the observation that, when asked to, reviewers were able to reliably sort more half of 300 items from the Adjective Checklist (Gough, 1960) into the Big Five traits (O. P. John, 1989). The HEXACO model (Ashton & Lee, 2007) as well is quite similar to other five-factor models, though it includes an Honesty-Humility scale (recovered from Big Five markers), yielding six factors.

Nonetheless, the Big Five garnered a consensus among personality psychologists and from there spread into the wider psychology community, being implemented as the de facto personality assessment (e.g., the Big Five Inventory; O. P. John et al., 1991).

More recently, however, skepticism of the Big Five has mounted (De Raad et al., 2010; Gurven et al., 2013; Laajaj et al., 2019). While it has maintained its stature among the broader psychology community, evidenced by its common use as a measure, personality structure theorists (even some early Big Five proponents) have recognized that the choice of five factors is somewhat arbitrary or mis-specified (Saucier & Iurino, 2020) and especially ungeneralizable (De Raad et al., 2010; Wood et al., 2020). Although some of the limitations of those early studies were described, the next section will provide a general framework of problems in lexical implementations and their mechanism in introducing structural error.

Limitations of Lexical Postulate Implementations

It is critical to note that the lexical postulate predates the evolution of personality discourse that organizes personality at multiple levels and various domains. The lexical postulate can be most readily recontextualized as providing a framework at the trait level. However, it was not initially conceived with such specificity and its implementations do not provide a clear delineation between traits and characteristic adaptations, especially since ratings by observers naturally lend themselves to the situational characteristics that brought people together to be observed in the first place. The utility of the lexical postulate—and reason for its survival thus far—is that it provides a means to a comprehensive set of traits. That utility would be greatly diminished if it yielded traits that are in fact not comprehensive or which greatly misrepresent the structure of personality, though neither can be determined by a lexical implementation. Moreover, a lexically-derived structure is effectively atheoretical and acausal. Though it lends itself to the interpretation that an underlying trait level causes its constituent descriptors, there are other conceptual links among trait descriptors (Cramer et al., 2012; Fleeson & Jayawickreme, 2015). Thus, while lexical implementations provide a valuable resource to personality research, they do not provide an explanatory or causal model of personality. Because of this, a lexical implementation alone is insufficient to answer many open questions in personality psychology but may provide a structure than can be used in service of answering those questions (e.g., finding biological bases for traits or studying trait development).

Potential limitations arise at numerous stages of implementing the lexical postulate. These stages include (1) the use of language itself, (2) the choice of language (often English), (3) the sample of participants (4) the choice of terms within that language, and finally (5) the analytic method for identifying factor. Some of these limitations are inherent to the lexical postulate, but most merely indicate a need for careful deliberation. Again, this dissertation addresses—and therefore focuses on—the last of those stages. However, the decisions informing data collection in a lexical investigation are likely more impactful, despite their brief treatment (to follow) in this work.

Language itself

First, the use language as the medium for inferring personality structure may be problematic as language is a social construction used instrumentally. Under this constraint, it is not necessary that the most fundamental individual differences be encoded into language, but rather the most fundamental individual differences that would be deemed relevant to communicate to others. This may induce a bias towards traits pertaining to social behavior (Trofimova, 2014). Indeed, one of the few actual tests of the validity of the lexical postulate found that lexical trait structures identify the important dimensions by which individual's shape their value to others (Wood, 2015). Personality is broader than just the dispositional traits or tendencies that tend to characterize lexically-derived models of personality. For example, *narrative identity* is regarded as a major domain of personality (Roberts & Yoon, 2022) .

Narrative identity reflects an individual's propensity to integrate their experiences into their personality (McAdams & McLean, 2013). If narrative identity were indeed a major domain of personality, then terms reflecting the traits that comprise narrative identity should be readily identifiable. Yet, it is difficult to think of a single term reflective of an aspect of narrative identity, let alone enough that it would be identified as a major part of personality through the lexical approach. To this author, only the phrase "main character syndrome"—denoting a pathological belief that one is the protagonist in life and others exist to play a supporting role (What is main character syndrome?, 2025)—comes close. Narrative identity, while vitally important to the individual, does not have the same obvious social import as *honest* or *industrious*, and may have eluded such simple encapsulation in a single word.

Among other domains, personality is generally agreed to include disposition, goals, values, interests, skills, and narratives (Rauthmann, 2024). These are vast areas that may be highly important to individuals yet may be omitted as single terms in a language. The inclination to explain this lack of overlap has been to explain *trait dispositions* as captured by trait adjectives, whereas others are not. Again, this does not seem well-established by the lexical postulate. Further, it is difficult to argue that values (e.g., *aesthetic*, *traditional*, *elitist, pious*) and interests (e.g., *bookish*, *outdoorsy, sporty*) are not represented as terms. If the lexical postulate is true, these domains of personality cannot be both important and largely unrepresented as single words.

Furthermore, language being a construct, many terms are abstract and unobservable. For instance, an individual can be observed as *fidgety* or *tense*, but to describe them as *anxious* or *uneasy* is to make a psychological inference. If the lexical postulate is that phenomena which are socially relevant become encoded into language, then a term such as *anxious* is not socially relevant in and of itself because it is secondary to its constituent behavior, which is actually the thing being observed and furthermore cannot be quantifiably compared across individuals (Uher, 2013). Despite the lack of objectivity across assessments of unobservable terms, people do so without pause. While only a minor hiccup in implementing the lexical postulate, these issues highlight that natural language use is not rigorous.

The use of single terms is itself problematic. Many terms are not well understood, but more importantly, even when they are, may exhibit idiosyncratic usage despite a general consensus; humans do not use language as a logical instrument (Block, 2010). For instance, the term *shallow* may indicate one with an interest in superficial aspect (a specific case being others' appearances), or a limited capacity for emotion, knowledge, reasoning, or interest. Thus, a person could be shallow in some ways and not at all in others, and the most salient aspects to the rater would determine their rating. Moreover, even in agreeing on a definition, two raters could differently quantify the same amount of shallowness in a person. Ultimately, the desire to construct a scientific construct from natural language use may be inherently flawed.

Language choice, or English

Second, samples and studies are overwhelmingly conducted in English. To be considered universal—which is often an implicit or even explicit view of empirically-derived personality models (e.g., McCrae & John, 1992)—personality models should be reasonably invariant to language, culture, and sample. Therefore, personality models should be informed by a wide breadth of languages, cultures, and participants. This is a difficult (and expensive) bar to clear.

Participant homogeneity

Third, participants especially should be heterogeneous in aspects such as nationality, education level, socioeconomic status, among others. In within the same language, culture varies as a function of many ecological factors (Triandis & Suh, 2002). However, tracing the lexical postulate from Thurstone (1934), to Allport & Odbert (1936), to Cattell (1943), to Tupes & Christal (1961), to Goldberg (1990), to Costa and McCrae (2008) reveals a preponderance of English language investigations, though there are notable exceptions to this (Angleitner et al., 1990; Ashton et al., 2004; De Raad et al., 2010; De Raad & Barelds, 2008).

Term selection

Fourth, assuming one aims to develop a structure of personality within a specific group sharing one language, the choice of terms used is greatly impactful, as those terms sum to define higher-order traits. A re-analysis of classical datasets (ranging in size from 75 to 1,710 terms) in personality structure research employing more empirically sound methods to identify the optimal number of factors found that the optimal number of factors was both somewhat heterogeneous across similarly-sized datasets and increased as a function of term set size (Saucier & Iurino, 2020). In that study, eight factors was the minimum recommendation, with a median estimate of 18—a far cry from the five factors initially identified by Fiske (1949). Had those studies been conducted when computing and factor analysis were more advanced, five factors might have been considered too few to represent personality.

All possible terms describing aspects of personality should be included in a lexical investigation. Identifying a structure of personality from a small set of terms introduces considerable researcher bias—particularly by omitting smaller domains of personality—and limits the scope of the structure. Selecting variables from a select number of pre-identified domains makes it likely that those domains will be recovered. Replicating patterns of covariance among a few small clusters of rationally related terms is neither unexpected nor a sufficient test of the lexical postulate, but when presented as such can influence future researchers' taxonomic decisions. This bias can propagate through re-use of those data or methods, eventually leading to a consensus around an illusory solution.

Selection of analytic methods

Lastly, the analytic methods applied during lexical investigations should be empirically validated to ensure they can appropriately reduce the dimensionality of extensive trait-variable datasets. Fully proving that a method is appropriate is a difficult (if not impossible) task, as it requires accounting for the data generating process upon which a lexical investigation may be hoping to shed light. At a minimum, distinct analytic approaches demonstrating congruence across solutions would demonstrate some hope that a structure of personality is not an artifact of analytic choice. This author is unaware of any studies assessing statistical validity against a proposed generative model. Even when comparing high performing dimension detection approaches, congruence is often limited (e.g., Saucier & Iurino, 2020) and relies on the researcher to make an informed decision.

Although this dissertation primarily grapples with analytic concerns, a nuanced understanding of the foundational aspects of any lexical investigation (e.g., the trait descriptive terms and the characteristics of participants) is necessary to fully appreciate the limitations of current of lexically-derived models of personality. Tracing the genealogy of the Big Five from lexically-derived models demonstrates violations of the best practices just described and that the supposedly universal structure of the Big Five is instead based on relatively few and methodologically constrained sources which show little universality when adequately tested. In the next section, I will describe the central arguments against the prominent Big Few models, focusing primarily on the methodological grounds for concern.

Re-appraising Past Lexical Investigations

The main criticisms against the methods of past lexical investigations have focused on the limited numbers of terms employed to ostensibly represent a comprehensive structure of personality, the re-use of terms or datasets in doing so, the predominance of English-language investigations, and the lack of diversity among participants despite the aim of a universal structure of personality. Each of these will be discussed in detail.

The starkest limitation of past works in this vein has been the repeated re-use of terms and ratings thereof. For instance, Fiske (1949), analyzed a set of 22 variables developed by Cattell and reproduced a set of five factors that closely resembles today's Big Five. Tupes & Christal (1961) analyzed sets of variables from Cattell and Fiske, as well as studies of their own Air Force officers on 35 terms selected by Cattell (1947). Norman (1963) replicated Tupes and Christal's findings using peer ratings on a set of twenty variables that best loaded onto the five factors identified by Tupes and Christal. Digman too (1981) re-analyzed classic studies, interpreting his findings as favoring the Big Five. Using such a small number of variables to represent personality is clearly not an adequate implementation of the lexical postulate, nor is it methodologically surprising that a small number of variables that were originally synonymously clustered can be represented by even fewer factors. Pre-structuring terms is especially concerning, as a large number of terms can be included while still largely guaranteeing that the structure by which they were selected will be recovered.

Modern discourse around the Open Science movement would categorize these as reproducibility—not replication—studies (Nichols et al., 2021; Nosek et al., 2022). Reproducibility tests the consistency of findings across the same data and methods, whereas replication tests consistency of findings more broadly (Condon et al., 2017). Although these studies by Fiske, Cattell, Norman, and others may have collected unique samples of ratings of terms, their use of a limited and overlapping set of personality terms constitutes the replication of a structure of personality *within that set of terms*, not the replication of a comprehensive structure of personality. Instead of interpreting their results as demonstrating that a comprehensive structure of personality can be reproducibly represented by the Big Five, an alternative perspective is that the Big Five—as a subset of personality—can be replicated, given a particular design, both in terms of measure and participants.

A common criticism of Big Few trait models derived from lexical investigations is their genesis in homogenous samples—both in language and demography. Such homogeneity is problematic to the extent that one wishes to generalize a personality structure. Unfortunately, that desire has historically been high (McCrae & Costa Jr, 1997). Much of the early work identifying the Big Five was done in English-speaking samples. To properly investigate the universality of the Big Five, cross-language investigations should be done. Cross-cultural comparisons of trait structural models generally follow an etic or emic approach. The emic approach situates personality structure indigenously, seeking a bottom-up approach. The etic (often called imposed-etic, when referring to cross-cultural comparison of the Big Five), aims to uncover universals across cultures. The former involves the usual process of a native speaker generating a list of personality descriptors to be empirically compared to other trait structures, based on content and psychometric qualities. In the latter, items based on an extant trait structure are translated and tested in another language. The etic approach is problematic as it assumes the same terms carry equal importance across cultures and thus can potentially exaggerate the importance of traits in the original language while missing ones in the language it was exported to. Cross-cultural investigations, particularly those taking an emic approach, have not reproduced the Big Five (Gurven et al., 2013; Thalmayer et al., 2020; Wood et al., 2020).

Stark personality differences between WEIRD (western, educated, industrialized, rich, democratic) and non-WEIRD samples can be found including trait-level differences, differences in predictive validity, and poorer reliability in non-WEIRD samples (Henrich et al., 2010; Laajaj et al., 2019). Psychology studies also employ a preponderance of undergraduate samples, which introduces similar issues (Arnett, 2008). Therefore, findings based on these samples should not be considered universal.

However, empirical evidence for the Big Five has historically been drawn from WEIRD samples. For example, Tupes and Christal (1961) employed samples of Air Force officers that skewed overwhelmingly male. Goldberg (1990) used samples of students in undergraduate psychology courses. Personality structure research owes a great deal to Goldberg, not only for his own research, but for making public some of his data, including the Eugene-Springfield Community Sample (Grucza & Goldberg, 2007). By the same token, however, a preponderance of insight into personality has been gleaned from a very small, specific group of participants in the Pacific Northwest United States.

Last, and most germane to this work, these studies all implemented variants of factor analysis as their analytic approach to identifying a structure of personality. In large part, this was due to factor analysis being a statistical method that could be implemented before computers—work by Thurstone and even Cattell was done by hand. As well, their means of identifying the optimal number of factors from these methods were limited. However, more advanced approaches are now widely available. While it would be unfair to criticize those past works for not making use of methods not yet developed, testing the validity and subsequent findings of alternative dimension reduction approaches would advance the lexical postulate paradigm.

Analytic Methods to for Dimension Reduction

Lexical investigations, at their core, have aimed to taxonomize trait descriptive adjectives, often to form a hierarchy of traits. A core step in this procedure has been to reduce the dimensionality of trait-descriptors such that an optimal number of groups of trait descriptors describing personality are identified.

In psychology, the constructs under investigation are often not directly observable and are therefore referred to as “latent variables.” A latent variable is an abstract construct that explains patterns in data. For example, the Big Five traits are latent variables explaining patterns of covariance in trait descriptors. The field of psychometrics has developed tools linking observable variables (often survey responses) to latent ones. One of the core techniques in psychometrics is factor analysis, which refers to a variety of methods aimed at assessing the dimensionality of the observed variables (indicators) in a set of data. In factor analysis, latent variables are termed factors—the dimensions by which variables largely vary. Assuming appropriate theoretical validity, these dimensions are thought to be informative of the phenomenology of the construct in question. Therefore, identifying the number of dimensions in a dataset has been a topic of serious investigation.

The field of dimension reduction has exploded since the time of Thurstone. In the most literal sense of methods designed for projecting high-dimensional data to lower-dimensional spaces, they include principal component analysis (Hotelling, 1936; PCA; Pearson, 1901), multidimensional scaling (MDS; Torgerson, 1952), t-distributed stochastic neighbor embedding (t-sne; Van der Maaten & Hinton, 2008), and Uniform Manifold Approximation and Projection

(UMAP; McInnes et al., 2018), though the latter two methods do not preserve distances well and therefore should be used for visualization, not clustering (Schubert & Gertz, 2017). In a looser sense, any method which can summarize data in fewer variables can be considered a dimension reduction approach, for which there are innumerable methods including clustering (itself a broad construct), community detection algorithms, and more.

In this work, methods of dimension reduction include (1) factor analysis, (2) clustering, (3) network psychometrics, and (4) a data science approach minimizing out-of-sample prediction error (*fspe*). Each of these methods – including multiple algorithms or instances of methods 1-3 – are evaluated in the context of personality structure in this dissertation. It should be noted that, regardless of the analytic approach or internal validity for a subsequent personality model, a factor solution is not self-reifying; factors are convenient summaries of covariances (Revelle, 1983). This general truth holds for any statistical model, though models can still be informative (Box, 1976).

It is certainly possible that analysis can delineate groups of differing etiologies to the extent that those groups are effectively "real" (e.g., Li et al., 2015). However, that subsequent confirmation requires substantively different experimentation to validate the insight gleaned from factor analysis. Further, this is almost certain not to be the case within the context of personality psychology. Factor models of personality may be used to generate such hypotheses (particularly aimed at identifying biological bases for personality traits), but in practice their use is in developing a relatively comprehensive, but tractable, personality assessment. In sum, a factor model is not inherently correct, nor based on any physical attribute, and its utility is contextual. Nonetheless, some methods of factoring are better than others.

Factor Analysis

Much of the work in studying the structure of personality has been reliant on exploratory factor analysis (FA) or principal component analysis (PCA). Both are procedures aimed at reducing a set of observed variables to a lesser set of new variables in such a way that these new variables can regenerate the initial correlation matrix among variables to the desired degree of precision (Block, 1995).

Principal components analysis assumes a model $R = \Lambda\Lambda'$, where R is the covariance matrix and Λ is the matrix of factor loadings. Eigen-decomposition is used to solve for Λ in PCA. It produces a representation of a matrix in terms of its eigenvalues and eigenvectors. Formally, a square matrix A can be factored as $A = Q\Lambda Q^{-1}$ where a column Q_i represents an eigenvector of A (direction by which A shrinks or elongates) and Λ is a diagonal matrix with eigenvalues (scalar for the extent of said shrinkage/elongation) of each eigenvector Q_i represented by Λ_{ii}. In the context where A is a correlation matrix, eigenvectors describe the axis by which variance is explained through a linear combination of variables and eigenvalues describe how much variance is captured by their correspondent eigenvector. In PCA, extracted components explain all variance. Put more simply, imagine fitting an ellipsoid to the observed data whose axes have the direction of the eigenvectors and length of their respective eigenvalues.

Factor analysis assumes a model $R = \Lambda\Lambda' + \Psi$, similar to PCA but adding Ψ, a diagonal matrix of unique variance. This produces a similar model, with the exception that diagonal elements of the correlation matrix are no longer one but represent communalities—variance shared among a set of items. There are numerous methods for estimating factors in FA, including Principal Axis Factoring (proceeding similar to PCA, once communalities have been estimated). Other prominent methods are ordinary least squares, generalized least squares, generalized weighted least squares, and maximum likelihood (Fabrigar et al., 1999). Estimation of factors is computationally trickier for FA, and therefore the easier method of PCA was used in its place before the computing revolution.

The fundamental difference between PCA and FA is that PCA aims to reduce dimensionality as a linear composite of observed variables, whereas FA assumes that observed variables are caused by latent factors, hence the use of communality. In the FA approach, identified factors explain common variance. The theory informing FA should make it preferential to researchers. In practice, the distinction is not always as important (Condon, 2018).

Factor analysis and PCA will extract as many factors as there are variables. Because dimension reduction is a goal of factor analysis, determining which factors to retain is a key aspect. There are numerous methods for selecting among potential solutions. Among the best is parallel analysis (Horn, 1965), which identifies the number of factors to keep by comparing the eigenvalues from the original dataset to eigenvalues from a Monte-Carlo simulated dataset. The data are generated from a Monte Carlo-simulated dataset with the same number of items and observations as the original data. Eigenvalues are extracted from both datasets. Factors from the original data with higher eigenvalues than the randomly generated data are considered significant and therefore retained. The intuition behind this test is that even random data can, through sampling variability, produce positive eigenvalues that can be used as a cutoff.

Parallel analysis is a relatively old method but is widely used and empirically performs much better than other common approaches (H. Golino et al., 2020). Examples of other methods include the Scree test (looking for an elbow in eigenvalue plots), Kaiser’s rule (extracting factors with eigenvalues greater than one), or Very Simple Structure (selecting the factor model based on goodness of fit when items can load only on to one factor; Revelle & Rocklin, 1979). In fact, numerous studies have demonstrated that—especially under certain conditions—parallel analysis performs either equivalent to, or not appreciably different from, more modern dimension detection algorithms, the likes of which are described later (Christensen, 2024; H. Golino et al., 2020; H. F. Golino & Epskamp, 2017). Early lexical investigations, however, used a variety of less-sound methods to determine how many factors to extract, including stopping when reaching a negative eigenvalue (e.g., Digman & Takemoto-Chock, 1981), scree analysis (e.g., L. R. Goldberg, 1990; Saucier & Goldberg, 1996), or achieving Very Simple Structure (e.g., E. Tupes & Christal, 1961).

Once factors have been extracted, how variables load onto each factor is determined through factor rotation. Factor rotation refers to a set of procedures aimed at reducing item complexity (the number of factors onto which items substantively load), which is commonly employed following factor extraction. Geometrically, this is the process of rotating the axes in factor space. Different rotations may substantially change how items load onto them, and thus the interpretation of which items are most associated with (i.e., belong to) which factors.

The biggest distinction between factor rotation methods is between orthogonal (e.g. varimax) vs oblique (e.g. oblimin) rotation. Geometrically, orthogonal solutions involve axes (factors) that are all at right angles to each other (in *n*-dimensional space). Thus, in those solutions, all factors are uncorrelated with each other. Oblique rotations relax the requirement of orthogonality; however, if the optimal solution is orthogonal, that solution will be produced. In this work, two oblique rotations (GeominQ and Oblimin) and one orthogonal (Varimax) are used.

There are numerous critiques of using factor analytic techniques as the basis for dimension reduction in a lexical investigation (Block, 1995). The critique this work hinges on is the empirically better performance of other approaches (H. F. Golino & Epskamp, 2017).

Clustering Algorithms

Though factor analysis has been the primary form of data reduction in works testing the lexical hypothesis, there are other approaches that accomplish a similar goal, including clustering. Clustering identifies similar groups of objects (e.g., clusters of survey items or terms) when group membership is not previously known. In doing so it assigns membership to these variables, although it may not provide a degree of membership strength as factor analysis does through factor loadings. The basis for clustering algorithms is distance between variables, which can itself be operationalized in many ways (e.g., Minkowski distance, Cosine distance, and Pearson correlation distance). Clustering based on a correlation matrix has been suggested (Revelle et al., 2011) but has not been largely adopted.

There are numerous clustering algorithms, each of which operates on different assumptions of the underlying data. In some sense, clustering algorithms differ in the implemented hypotheses of trait representations and may recover very different structures. Assumptions may define the number of clusters to be found explicitly or implicitly based on researcher-defined parameters.

Cluster geometry is also a major consideration, as clusters may differ drastically in size and shape. Clustering algorithms such as *k*-means (and other partitional algorithms) are not well specified for datasets where the optimal clusters are non-convex or of unequal sizes. It is difficult to predict the shape of trait clusters in embedding spaces. Studies have demonstrated unequal numbers of terms in their superordinate traits (Cutler & Condon, 2022; L. R. Goldberg, 1990).

Further, some clustering algorithms are better suited to handling noisy data or outliers better than others. Therefore, clustering algorithm selection is highly based on the use case.

The most straightforward evaluation of a cluster solution is to evaluate tightness (distance of items in a cluster) and separation (distance between clusters), with the ideal solution maximizing separation, while minimizing distance (Hall, 2012). Ideally, this would result in groups of data sorted into distinct classes, such that data with similar attributes are in the same class.

Although clustering algorithms implement different hypothetical models and therefore it is difficult to say one is wrong or right, some algorithms tend to have better empirical performance than others. Clustering, as a subset of the wider dimension reduction field, has also undergone rapid advances in the past couple decades. Spectral Clustering (Ng et al., 2001) and HDBSCAN (Campello et al., 2015) are two such examples. Even more recently, algorithms employing deep learning have been used for clustering (Ren et al., 2024).

Describing and testing all existing clustering algorithms is a task both unwieldly, given the number of algorithms, and quickly irrelevant, as the development of new algorithms is rapid. For the sake of maintaining feasibility, I focus on the some commonly used algorithms. This includes early foundational algorithms such as Ward's minimum-variance clustering (Ward Jr, 1963) and average linkage clustering (Sokal & Michener, 1958), as well as modern, high-performance algorithms such as HDBSCAN (McInnes et al., 2017), spectral clustering (Ng et al., 2001), affinity propagation (Campello et al., 2015), and Gaussian Mixture Modelling.

Ward's minimum variance and average linkage are comparatively simple algorithms, joining nodes to either minimize variance from cluster centroids or pairwise distances within clusters, respectively. Nonetheless, the rationale of such methods can be effective in dimension reduction (Christensen, 2020) and still underlies high-performing algorithms such as the Walktrap method (Pons & Latapy, 2006). The remaining algorithms of spectral clustering, affinity propagation, HDBSCAN, and gaussian mixture modelling, were selected for their high performance, breadth of methods, and popularity (Ding et al., 2024; Refianti et al., 2016; M. Z. Rodriguez et al., 2019; Zhang et al., 2021).

Traditional Clustering Algorithms

Ward's minimum-variance clustering and average linkage provide a simple entry into clustering algorithms. Both implement different algorithms for agglomerative (bottom-up) hierarchical clustering to decide on clusters as they aggregate a hierarchy of clusters. They seek to iteratively combine data points into sets called *clusters*. Both start with a set of data in which each data point can be considered its own cluster. Clusters will then be merged to form larger clusters. In these algorithms, once points have been clustered together they will not be separated, but clusters themselves will become merged until all points have ultimately been subsumed under one cluster. Therefore, the criterion for how to decide which clusters to merge essentially defines the algorithm. In this work, I use Ward's minimum-variance clustering and average linkage.

Ward's Minimum-Variance Clustering

This method merges clusters by minimizing the increase in within-cluster sum of squares (WSS), where within-cluster sum of squares is defined as:

Equation 1

$$WSS = \sum_{i=1}^{k} \sum_{x \in C_i} \lVert x - \mu_i \rVert^2$$

Where μ_I is the centroid for cluster *i*. Thus, the change in WSS by merging clusters A and B is defined by:

Equation 2

$$d_{Ward}(A, B) = WSS(A \cup B) - WSS(A) - WSS(B)$$

This algorithm merges clusters such that the increase in variance around each cluster's centroid is minimized.

Average Linkage

Average linkage (unweighted pair group method with arithmetic mean) seeks to evenly minimize all pairwise distances in a cluster. Formally, for clusters *A* and *B*, the average distance is given by:

Equation 3

$$d_{avg}(A, B) = \frac{1}{|A||B|} \sum_{x \in A} \sum_{y \in B} d(x, y)$$

where d(x,y) is usually Euclidean distance. Clusters are merged by selecting the two clusters whose average pairwise distance between all members is smallest.

These algorithms will produce a hierarchy of clusters which can be visualized as a dendrogram. However, because each will produce a partition for cluster solutions of 1 to *k* (where *k* is the number of datapoints), an additional measure is needed to select a single flat partition. In the absence of some ground truth to compare the cluster partitions against, an internal validity index is used to select the partition. Internal validity indices select for an optimum within some measure of partitions. There are numerous internal validity indices, but overall they seek to maximize compactness and separation of clusters while minimizing the overall number of clusters (Y. Liu et al., 2010). In this work, the Krzanowski-Lai (1988) and Davies-Bouldin (1979) indices are used as internal validity indices.

Krzanowski–Lai (KL) Index

Because an increasing number of clusters generally allows for a decreasing within-cluster sum of squares (due to more clusters more tightly fitting the given data), the Krzanowski–Lai index aims to identify an elbow in the function of within-cluster sum of squares across cluster number. It uses a “second-difference” of the total within-cluster sum of squares to select *k*. It proceeds as such:

1. Compute within cluster sums of squares:

Equation 4

$$SS_W^{(k)} = \frac{1}{|A||B|}\sum_{i=1}^{k}\sum_{x\in C_i}||x-\mu_i||^2$$

2. Define the scaled differences:

Equation 5

$$\mathrm{DIFF_k} = (k-1)^{2/J}\,\mathrm{SS_W^{(k\text{-}1)}} - k^{2/J}\,\mathrm{SS_W^{(k)}},$$

where J is the number of variables. This quantity measures the drop in scaled within-cluster dispersion going from *k-1* to *k* clusters.

3. The KL index is then defined as

Equation 6

$$\mathrm{KL_k} = \left|\frac{\mathrm{DIFF_k}}{\mathrm{DIFF_{k+1}}}\right|.$$

The optimal *k* is selected for by finding the maximum of this index.

Davies–Bouldin (DB) Index

Davies-Bouldin index operationalizes a measure of interclass-intraclass separation. This measure finds the worst case of this separation for each cluster in a partition, then averages across clusters.

1. For each cluster C_i with centroid μ_i, compute the average scatter (distance) —which can be thought of as the intraclass separation component—as:

Equation 7

$$S_i = \frac{1}{|C_i|} \sum_{x \in C_i} \|x - \mu_i\|$$

2. Between-centroid distance—the interclass component—is computed by:

Equation 8

$$M_{ij} = \left\|\mu_i - \mu_j\right\|$$

3. Pairwise similarity then becomes the ratio of the prior elements:

Equation 9

$$R_{ij} = \frac{S_i + S_j}{M_{ij}}$$

4. The worst case for each cluster *i* is selected:

Equation 10

$$R_i = \max_{j \neq i} R_{ij}$$

5. Ultimately, leading to the Davies–Bouldin index as the average of R_i across clusters:

Equation 11

$$DB = \frac{1}{k} \sum_{i=1}^{k} R_i$$

HDBSCAN

HDBSCAN provides an interesting example of the advances of clustering algorithms. It implements a density-based method of clustering. Density-based clustering algorithms are non-parametric and make no assumptions about the underlying number of clusters in data, nor their shapes ("Density-Based Clustering," 2016). This approach to clustering can be traced back at least to Wishart (1969), but was introduced to computer science through a predecessor to HDSCAN, DBSCAN (Ester et al., 1996). DBSCAN aimed to address some key limitations of traditional algorithms such as K-means, which struggle to identify non-convex geometries or noise points. By comparison, DBSCAN finds arbitrary shapes of dense areas of nodes that it identifies as clusters, that are separated from other distant clusters and unclustered points. It takes as parameters radius and minimum points. Each node is considered as a start of a cluster—if that node has at least the minimum points within the determined radius, it is marked as a core point. Those other points within that radius are then similarly evaluated, and so a cluster is propagated until outlier points which are identified within the radius of a core point, but without enough neighbors to themselves be a core point. Points which are not within the radius of a core point are considered unclustered noise. This algorithm is still effective (Schubert et al., 2017), but provides only a single partition. This motivated the development of HDBSCAN, which uses only a single parameter, minimum number of points, to develop a hierarchy of clusters across distances, then selects the most stable clusters across that hierarchy to generate a flat partition. It proceeds as such:

1. Core & Mutual-Reachability Distances

Core distance for a point x is defined as:

Equation 12

$$d_{\text{core}}(x) = \text{distance from } x \text{ to its } k^{\text{th nearest neighbor}}$$

Where k is the minimum cluster size. Mutual-reachability distance is then the distance between two points *x* and *y*, defined as:

Equation 13

$$d_{\text{mreach}}(x, y) = \max\{\, d_{\text{core}}(x),\, d_{\text{core}}(y),\, d(x, y)\}$$

2. Building the Minimum Spanning Tree (MST)

Compute the graph on your data where every pair (*x,y*) is connected by an edge weight. Extract the MST, defined as the shortest path through all mutually reachable vertices.

3. Trim the Cluster Tree

Descend down a density parameter λ. At each step, remove the longest edge in the MST, cleaving a cluster. Record the birth/death of clusters, generating a persistence dendrogram.

4. Stability-Based Cluster Selection

Each cluster has a stability value defined by:

Equation 14

$$\text{stability}(C) = \sum_{x \in C} \left(\lambda_{\text{birth}}(x) - \lambda_{\text{death}}(C)\right)$$

HDBSCAN selects the set of non-overlapping clusters that maximize total stability. Unassigned points are considered noise (unclustered points). HDBSCAN therefore can discover clusters of different densities, handle noise, and automatically select a preferred clustering. As well, it identifies a hierarchy of clusters.

Spectral Clustering

Spectral clustering uses eigendecomposition to project the graph Laplacian (a form of network graph) of a similarity matrix into a lower-dimensional space and cluster on that new embedding. It follows as such:

1. Compute the graph Laplacian. Common choices are unnormalized

Equation 15

$$L = D - A$$

or the symmetric normalized

Equation 16

$$L_{\text{sym}} = D^{-1/2} L D^{-1/2}$$

where *D* is the diagonal matrix of node degrees and *A* is the adjacency matrix.

2. Extract the first *k* eigenvectors of *L* and form the matrix $U \in R^{n \times k}$.

3. Cluster within that reduced embedding space. K-means is a common choice. In the *Spectrum* package (C. R. John & Watson, 2020), choice of *K* is determined using eigengap, multimodality gap, or user-selected methods. In this work, the former two are used. Spectral clustering has achieved high performance. It can capture non-convex cluster shapes. However, eigen-decomposition can be computationally expensive.

Affinity Propagation

Affinity propagation attempts to find “exemplar” points that characterize clusters. It functions by “message passing” between data points. Points exchange two kinds of messages—responsibility (how suitable a candidate exemplar is for that point) and availability (how much that candidate is supported by other points). This process iterates until convergence at which point the highest combined responsibility and availability pairs reveal which points become exemplars.

1. Generate a Similarity Matrix

Starting with a matrix S∈ $R^{n \times n}$, where

Equation 17

$$S_{ij} = s(i,j)$$

measures how well point *j* is suited to be the exemplar for point *i*.

2. Update Responsibility Messages *r(i,k)*

The responsibility *r(i,k)* reflects the accumulated evidence for how well-suited candidate *k* is to serve as the exemplar for point *i*, taking into account other potential exemplars. It is updated as:

Equation 18

$$r(i,k) \leftarrow S_{ik} - \max_{k' \neq k}\{a(i,k') + S_{ik'}\}$$

Where S_{ik} is the raw similarity of *k* for *i*, and $\max_{k' \neq k}\{a(i,k') + S_{ik'}\}$ is the best alternative exemplar for *i*, including its availability.

3. Update Availability Messages *a(i,k)*

The availability *a(i,k)* reflects how appropriate it would be for point *i* to choose *k* as its exemplar, taking into account support from other points that *k* should be an exemplar. It's updated as follows:

For $i \neq k$:

Equation 19

$$a(i,k) \leftarrow \min!\left\{0,\ r(k,k) + \sum_{i' / \in \{i,k\}} \max\{0, r(i',k)\}\right\}$$

For the self-availability *a(k,k)*:

Equation 20

$$a(k,k) \leftarrow \sum_{i' \neq k} \max\{\, 0,\, r(i',k)\}$$

Here, *r(k,k)* is how much point *k* favors itself as an exemplar. The component $\sum_{i' \neq i,k} \max\big(0, r(i',k)\big)$ is how strongly other points want *k* as an exemplar. Taking $\min\{\, 0,\, \ldots\}$ for off-diagonal avoids over-counting when support is weak. Responsibility and availability matrices *r* and *a* are alternatingly updated until convergence (or a fixed number of iterations is reached).

4. Exemplar and Cluster Assignment

Once messages have stabilized, each point *i* chooses exemplar

Equation 21

$$\hat{k}(i) = \arg\max_{k}\{a(i,k) + r(i,k)\}$$

Points with the same choice *i* are in the same cluster.

Exemplar-based clustering is especially convenient for the psycholexical postulate in that it provides a suggestion for interpreting the content of a cluster (i.e., it identifies the term that best exemplifies the cluster). However, it is most effective through tuning preference level, which is not preferred, as it biases the solution towards a certain *k* for the given data.

Gaussian Mixture Modelling

Gaussian Mixture Modelling (GMM) assumes that the data is generated from a mixture of K Gaussian distributions, each with its own mean, covariance, and mixing proportion. It assumes a probability density function of:

$$p(x) = \sum_{k=1}^{K} \pi_k \; \mathcal{N}(x_i | \mu_k, \Sigma_k)$$

Where x_i is a data point, π_k are the mixing proportions, μ_k are the component means, and Σ_k are the covariance matrices. The algorithm proceeds in two steps of Expectation Maximization (EM): the E-step computes the posterior probability that each data point x_i belongs to each cluster *k:*

$$\gamma_{ik} = \frac{\pi_k \, \mathcal{N}(x_i | \mu_k, \Sigma_k)}{\sum_{j=1}^{K} \pi_j \; \mathcal{N}(x_i | \mu_j, \Sigma_j)}$$

given current parameter estimates, while the M-step updates the parameters (means, covariances, and mixing proportions) to maximize the likelihood given the current cluster assignments. It fits multiple models with different numbers of clusters (K) and different covariance structures (spherical, diagonal, ellipsoidal, etc.) and selects the optimal combination using the Bayesian Information Criterion (BIC). This approach provides uncertainty quantification through posterior probabilities and can capture elliptical cluster shapes of varying orientations and sizes. However, GMM assumes that clusters follow Gaussian distributions, which may not hold for all datasets, and the EM algorithm can be sensitive to initialization and may converge to local optima. Initialization of EM is performed using partitions from agglomerative hierarchical clustering.

Table 1. Summary of Clustering Algorithms

Clustering Algorithm	**Mechanism**	**Partition Selection Criterion Implemented**	**Notes**
Ward's Minimum Variance	Minimizes sum-of-squared differences from cluster centroid.	Davies-Bouldin or Krzanowski-Lai Index	Basis for Walktrap; foundational method in clustering

Average Linkage	Aggregates nodes to minimize pairwise distances.	Davies-Bouldin or Krzanowski-Lai Index	Foundational method in clustering.
HDBSCAN	Builds a hierarchy of clusters at different density levels and extracts clusters that persist across density thresholds	Stability value	Handles various geometries and densities.
Spectral Clustering	Clusters projection of graph Laplacian based on similarity matrix.	Eigengap or multimodality gap	High performance, handles different geometries.
Affinity Propagation	Iteratively passes messages between data points to determine which points serve as exemplars for others.	Built-in; can be tuned	Identifies exemplars of clusters.
Gaussian Mixture Modelling	Identifies clusters from fitting different numbers of gaussian distributions to points	Bayesian Information Criterion	Also provides a generative model.

Network Psychometrics

Network psychometrics (Epskamp et al., 2017), in which variables are thought to be directly causally related to each other instead of sharing a common factor, has recently gained prominence in the field. Though it bears a strong resemblance to some clustering methods (indeed, it can be thought of as such), it has both a specific methodological approach that deserves unpacking and a suite of tools and research behind it to merit separate discussion. It allows for similar inferences to exploratory factor analysis, while employing network approaches. This approach has been termed *exploratory graph analysis*.

Exploratory graph analysis involves two broad steps: first, estimating a network from a covariance matrix, represented as a graph of connections among nodes; and second, applying a community (network-theoretic term analogous to *factor*) detection algorithm, of which there are numerous. A community is a group of highly interconnected nodes within a network that are less connected to other outside communities. Community detection algorithms are essentially a subset of clustering algorithms that have been validated for network graphs.

Community detection accomplishes the same goal as factor analysis, since both aim to identify how patterns of how variables covary. In network psychometrics, clusters of variables are analogous to the latent variable in factor analysis, and network loadings (strength of a node within a community) are analogous (and empirically equivalent) to factor loadings.

Network psychometrics have achieved state-of-the-art performance on dimension reduction tasks (H. Golino et al., 2020; H. F. Golino & Epskamp, 2017). This is the main reason for their inclusion. However, their performance is highly variable depending on factors including within-factor to between-factor covariance strength, number of total variables, differing numbers of variables per factor, and sample size (H. Golino et al., 2020). Network methods are usually tested on datasets with more variables (sizes of 10^3-10^6) and have yet to be specifically evaluated for their performance in the context of a lexical investigation for personality structure.

Regularized Network Approaches

Network graphs in exploratory graph analysis are estimated from regularized partial correlation networks (Epskamp & Fried, 2018). A partial correlation (the relationship between two variables after control for other variables) coefficient is thought to indicate the direct relationship between variables and therefore is the basis for a causal network (graph) among variables. In the parlance of exploratory network analysis, network graphs derived from partial correlations are referred to as *Gaussian Graphical Models* (GGMs). Although a network graph can be estimated by inverting the sample variance-covariance matrix, more often they use a regularized estimation method to avoid unstable parameter estimates due to overfitting.

Regularization is a set of techniques that penalize model complexity to avoid overfitting. In the case of networks, complexity refers to edges between nodes, and so regularization attempts to remove spurious edges, yielding a sparse network. Regularization approaches differ in how they penalize coefficients, producing varying networks. In particular, the use of the eBICGLASSO (Epskamp & Fried, 2018) —referring to the extended Bayesian information criteria (eBIC) hyperparameter selection criterion and graphical lasso (GLASSO) regularization (Friedman et al., 2008) —to generate a sparse precision matrix (from which a network is estimated), may not be an optimal approach, as the assumptions for GLASSO regularization (e.g., network sparsity, observations<variables) may not match those in psychology research (D. R. Williams & Rast, 2020). Different penalty types, or even different methods other than regularization for estimating a partial correlation network, may more accurately retain edges (D. R. Williams & Rast, 2020).

Various networks are produced at different levels of regularization. Therefore, an information criterion (IC) is used to select a single network on which a community detection algorithm will be run.

Regularization approaches considered in this work are GLASSO, Atan, Adaptive Lasso, Log penalty and Fisher Z-transformed confidence intervals. Treatments of each follow.

Graphical Lasso (GLASSO)

The graphical lasso, as described previously, directly estimates a sparse precision (inverse-covariance) matrix by applying an ℓ_1 penalty (it penalizes the total sum of coefficients) to its off-diagonal elements. GLASSO regularization limits the sum of the absolute partial correlation coefficients in a precision matrix K by maximizing the penalized likelihood function:

Equation 22

$$\log\det(\boldsymbol{K}) - \operatorname{trace}(\boldsymbol{SK}) - \lambda \sum_{<i,j>} |k_{ij}|$$

Where S represents the sample variance-covariance matrix. Different values of λ produce different network estimations, where a higher λ induces a sparser network. Selecting from these networks depends on an additional criterion. In the case of EBICGLASSO, the criterion used is the extended Bayesian information criterion (eBIC), in which λ is selected to minimize eBIC (Chen & Chen, 2008). The eBIC method itself has a hyperparameter γ, for which the usual selection is .5 (Epskamp & Fried, 2018). This yields a convex optimization problem (one local maximum in the loss penalty) whose solution is both sparse (few non-zero edges) and guaranteed positive definite.

This method was primarily developed for identifying relationships among variables under dataset conditions in which the number of variables is larger than the number of observations. Under those conditions, least squares parameter estimates are not unique, hence the need for regularization. These conditions are not common to psychological research, where, conversely, the number of observations is generally far greater than the number of variables. Further, this method can perform sub-optimally with highly intercorrelated data (D. R. Williams & Rast, 2020). Estimation errors also do not shrink with increasing sample sizes (Epskamp & Fried, 2018). Nevertheless, the EBICGLASSO approach to regularization is a prominent one in network psychometrics, partially due to being championed by leading authors in the area, but also for performing well in their simulation studies (Epskamp & Fried, 2018; H. F. Golino & Epskamp, 2017).

Atan

Arctangent (Atan; Wang & Zhu, 2016) regularization penalizes a model's loss function based on the arctangent of the weights to provide an estimate of coefficients $\hat{\beta}$. This penalty is defined by:

Equation 23

$$\hat{\beta} = arg\min_{\beta} \frac{1}{2n}\|y - \mathrm{X}\beta\|^2 + \lambda\left(\gamma + \frac{2}{\pi}\right)\tan^{-1}\left(\frac{|\beta|}{\gamma}\right)$$

In which β is the coefficient vector, X is the design matrix of predictors, y is a vector of response variables, λ is the tuned penalty parameter, and γ is the shape parameter. This penalty closely approximates the l_0 penalty, which penalizes the number of coefficients. That is to say, it identifies a subset of coefficients. This type of penalty is obviously attractive for generating a spare precision matrix but has computational drawbacks due to being non-continuous around zero, as well as the loss function being non-convex (may have multiple local minima, complicating optimization), and therefore, computationally difficult. The implemented algorithm uses an iteratively re-weighted lasso algorithm with a BIC-like tuning parameter to optimize the λ hyperparameter. This method does not appear to have been employed in psychological research.

Log

The log penalty regularization is a generalization of the elastic net family. It is a non-convex penalty that includes a shape parameter $\gamma>0$, where the penalty approaches ι_0 as $\gamma \to \infty$.

Equation 24

$$\hat{\beta} = arg \min_{\beta} \frac{1}{2n} \|y - X\beta\|^2 \; + \frac{\lambda}{\gamma} \sum_{j=1}^{p} log\left(1 + \gamma\left|\beta_j\right|\right)$$

For each value of λ (as λ increases from 0^+ to ∞) we get the entire continuum of penalties from l_1 to l_0 (Mazumder et al., 2011).

Adaptive Lasso

The adaptive lasso, also a non-convex method, modifies the usual ι_1 penalty (the second term in the equation) by re-weighting the coefficients according to ϖ_j:

Equation 25

$$\hat{\beta} = arg \min_{\beta} \frac{1}{2n} \|y - X\beta\|^2 \; + \lambda \sum_{j=1}^{p} \omega_j \left|\beta_j\right|$$

Where ϖ_j is often chosen as $\frac{1}{\hat{\beta}(OLS)}$. The rationale behind this is that larger absolute beta coefficients should be less likely to be spurious and therefore ought to be retained. To facilitate this, the adaptive lasso penalty ϖ_j shrinks as beta increases.

Fisher Z-transformed Confidence Interval Selection

This method, proposed by Williams and Rast (2020) aims to identify a partial correlation matrix. In it, one first computes the *p* x *p* covariance matrix using maximum likelihood estimation defined by:

Equation 26

$$\Sigma = \left[\frac{1}{N} \sum\nolimits_{i=1}^{n} (x_i - \overline{x})(x_i - \overline{x})^T\right]$$

Partial correlations are obtained as the standardized conditional relationships:

Equation 27

$$\rho_{ij} = \frac{-\theta_{ij}}{\sqrt{\theta_{ii}\theta_{jj}}}$$

To determine the partial correlations that should be set to zero, the partial correlations are transformed using the Fisher Z-transformation, which results in an approximate normal distribution. Confidence intervals for the z-transformed data are computed for z_{ij} as

Equation 28

$$Z_L = z_{ij} - Z_{\alpha/2}\sqrt{\frac{1}{n-3-s'}}$$

Equation 29

$$Z_U = z_{ij} + Z_{\alpha/2}\sqrt{\frac{1}{n-3-s'}}$$

These intervals are transformed back into partial correlations according to:

Equation 30

$$\widehat{\rho_{ijL}} = \frac{e^{2Z_L}-1}{e^{2Z_L}+1}$$

Equation 31

$$\widehat{\rho_{ijU}} = \frac{e^{2Z_U}-1}{e^{2Z_U}+1}$$

Confidence intervals for $\hat{\rho}_{ij}$which exclude zero are included in the final edge set. This approach outperformed the eBICGLASSO approach in both limiting spurious edges and retaining true edges in one study (D. R. Williams & Rast, 2020). That same study further found that specificity of edges in model selection by the eBICGLASSO method decreased as a function of sample size—a concerning finding mirrored by Kuisman and Sllanpää (2016).

Convex Methods

Those previously described regularization methods (with the exception of GLASSO) are best applied to low-dimensional data (ideally, much less than 1,000 variables) and scale poorly. High-dimensional Gaussian graphical model selection requires methods that balance statistical accuracy, computational efficiency, and ease of tuning. For the higher-dimensional studies, this work employs four popular, convex or near-convex approaches—Meinshausen–Bühlmann neighborhood selection (MB), graphical lasso (GLASSO), correlation thresholding (CT), and tuning-insensitive graph estimation (TIGER). These methods are more computationally efficient.

Meinshausen-Bühlmann Neighborhood Selection (MB)

Meinshausen and Bühlmann (2006) proposed treating each variable's conditional dependencies as a separate sparse regression problem. Rather than estimating the full precision matrix at once, *p* independent lasso regressions—one for each node—are fitted, predicting that node from all others. Nonzero regression coefficients indicate conditional dependence edges, which are then symmetrized into a final undirected graph. This is implemented by solving the lasso-penalized least-squares problem for each node j:

Equation 32

$$minimize_{\beta_{-j}} n^{-1} \left\| X_j - X_{-j}\beta_{-j} \right\|^2 + \lambda \left\| \beta_{-j} \right\|^1$$

Where X_{-J} is the $n \times (p-1)$ matrix of all other variables. Coefficients where β is not zero imply a candidate edge between nodes j and k. The final graph is "symmetrized" via a union or intersection rule. This approach is parallelizable and avoids large-matrix inversion, but its two-stage nature (regression then symmetrization) can produce ambiguous edge assignments if λ is not carefully chosen. Selection for λ can be done by cross-validation (minimizing prediction error), information criteria, or stability selection (e.g. STARS).

Tuning-Insensitive Graph Estimation (TIGER)

TIGER (H. Liu & Wang, 2017) uses the scaled Lasso for each nodewise regression, which automatically adapts the penalty to the noise scale and dimensionality. It sets the penalty to a universal constant times √(ln p/n), removing the need for expensive cross-validation or information-criterion tuning.

For each node j, solve the scaled Lasso:

Equation 33

$$min_{\beta,\sigma}\ \left\|X_j - X_{-j}\beta\right\|^{22}/(2n\sigma) + \sigma/2 + \lambda^0\|\beta\|^1$$

Where $\lambda^0 = C \cdot \sqrt{(ln\, p\,/\,n)}$.

This regularization process is tuning-free, as the penalty has been established theoretically (H. Liu & Wang, 2017)**.** However**,** a universal penalty can be overly conservative in moderate dimensions and of course is less flexible if one wishes to vary sparsity manually. These regularization approaches are summarized below (Table 2).

Table 2. Summary of Regularization Methods

Regularization Approach	**Mechanism**	**Convex?**	**Notes**
GLASSO	Applies penalty λ to off-diagonal elements in precision matrix.	Yes	Standard approach for EGA.
Atan	Applies arctangent penalty.	No	Approximate l_0 penalty.
Log	Applies logarithmic penalty/	No	Generalizes elastic net regularization.
Adaptive Lasso	Re-weights lasso to lessen penalty on large coefficients.	No (initial weight estimates are not convex)	Favoring large partial coefficients has face validity.

Fisher Z-Transform	Z-transforms edges in precision matrix, including those whose upper and lower bounds do not overlap zero.	No	Has some evidence for favorable performance compared to GLASSO.
MB	Fits lasso regressions for each node.	Yes	Computationally efficient.
TIGER	Similar to MB, but uses automatic thresholding to be less sensitive to choice of penalty.	Yes	Incorporates automatic thresholding.

Information Criteria

In graph-selection problems, including among Gaussian graphical models, we estimate a sparse precision matrix by applying a regularization path along a tuning parameter. We then choose a single tuning parameter λ by minimizing an information criterion that balances model fit against complexity. This provides a single solution to the graph, which is then used with community detection algorithms. Here the model complexity is typically measured by the number of edges and the fit is measured by the Gaussian log-likelihood. Each information criterion yields a different trade-off between false positives (extra edges) and false negatives (missing true edges). The criteria employed in this study are described below.

Bayesian Information Criterion (BIC)

The Bayesian Information Criterion (BIC) is intended to approximate the log of the marginal likelihood under a Laplace approximation. As is the goal of using information criteria to select a model, it rewards good fit (high likelihood) but penalizes model complexity (number of parameters) as a function of sample size. In practice, BIC tends to select simpler models than AIC, especially in cases of a large n. It is formalized by:

Equation 34

$$BIC = -2\ln L\left(\hat{\theta}\right) + E\ln n$$

In which ln $L(\theta)$ is the maximized log-likelihood, E is the number of non-zero edges, and n is the sample size. As can be seen, changes to the log-likelihood must more than offset the penalty introduced by added parameters in order to constitute a net improvement under the BIC.

Extended Bayesian Information Criterion (eBIC)

In high-dimensional settings (more variables than observations—$p>>n$), even BIC can overfit by selecting too many parameters. eBIC adds an extra combinatorial penalty, controlled by γ, that increases sparsity. The eBIC is widely used in graphical model selection (e.g. GLASSO) and variable selection when p is large.

Equation 35

$$eBIC(\gamma) = -2\ln L\left(\hat{\theta}\right) + E\ln n + 4\,\gamma E\ln(p)$$

In which p is the number of variables (nodes), E is the number of non-zero edges, n is the sample size, and $\gamma \in [0,1]$ tunes the extra combinatorial penalty.

When p is large (often $p \gg n$), the term $4\gamma|E|\ln(p)$ heavily penalizes graphs with many possible edge-subsets. It can be readily seen that with $\gamma=0$ the regular BIC is recovered; $\gamma=0.5$ is the "default" eBIC used in GLASSO; increasing γ further yields even sparser graphs. The eBIC is the most popular information criterion in graphical Lasso workflows.

Generalized Information Criterion 3 (GIC_3)

GIC_3 (as operationalized in the *GGMncv* package) penalizes the log-likelihood using the term 2log(p). It is useful when BIC still overfits in moderately high-dimensional settings when an EBIC-style combinatorial term isn't desired. It has the formula:

Equation 36

$$GIC_3(\gamma) = -2 \ln L\left(\hat{\theta}\right) + E\ 2\ \log(p)$$

In which ln *L(θ)* is the maximized log-likelihood, *E* is the number of non-zero edges, and *p* is the number of nodes.

Generalized Information Criterion 4 (GIC_4)

GIC_4 (also from *GGMncv*) extends the idea of GIC_3 with an additional double log penalty. It is primarily suited to very high-dimensional problems; in lower-dimensional cases, it will approximate GIC_3. It has the formula:

Equation 37

$$GIC_4(\gamma) = -2 \ln L\left(\hat{\theta}\right) + E\ 2\ \log(p) + log(\log(p))$$

Using the same parameters as the GIC_3.

The GICs are used for the non-convex regularization methods (log, Atan, adaptive lasso). In addition to the eBIC and BIC criteria, one additional criterion—Rotation Information Criterion—is added for the MB, GLASSO, and TIGER regularization methods.

Rotation Information Criterion (RIC)

Rather than counting parameters, RIC evaluates the stability of the estimated precision matrix under random orthonormal rotations of the data. For each candidate λ, one computes:

Equation 38

$$RIC(\lambda) = (1/B) \sum_{b=1}^{B} \left\| R_b\, \Theta(\widehat{\lambda})\, {R_b}^{\mathrm{T}} - \Theta(\widehat{\lambda}) \right\|_F^2$$

Where R_B are B random rotation matrices and $\|\cdot\|_F$ is the Frobenius norm. The λ that minimizes RIC yields an estimate that is most invariant to these rotations—i.e. most stable under changes of basis. RIC does not rely on likelihood-based penalties or combinatorial terms but can be more computationally intensive (due to multiple matrix-multiplication and norm calculations). It is appealing when the primary concern is robustness of edge recovery rather than strict information-criterion minimization. A summary of information criteria is presented below (Table 3).

Table 3. Summary of Information Criteria

Information Criteria	Mechanism	Notes	Selects Network from Regularization Approaches
BIC	Penalizes non-zero edges based on sample size.	Special case of eBIC.	GLASSO, Atan, Log, Adapt, MB, TIGER
eBIC	Same as eBIC but adds extra penalty (determined by γ) for large number of variables.	Standard approach in EGA.	GLASSO, Atan, Log, Adapt, MB, TIGER
GIC_3	Penalizes large sets of variables as in eBIC but uses log-based penalty term.		GLASSO, Atan, Log, Adapt
GIC_4	Provides additional log penalty for an even stronger penalty than GIC_3.		GLASSO, Atan, Log, Adapt, MB, TIGER
RIC	Maximizes invariance to random rotation.	Only used in convex methods.	GLASSO, TIGER, MB

Community Detection Algorithms

Having identified a network, different community detection algorithms are then applied to identify the nodes and their respective communities. There are numerous community detection algorithms (e.g., Spinglass, Isomap, Fast-Greedy), but the ones included in the studies within this dissertation are the Louvain, Leiden, and Walktrap algorithms, having been selected for their empirical performance in network psychometric contexts (H. Golino et al., 2020).

Louvain

The Louvain algorithm is a widely-used and computationally-efficient clustering algorithm that employs a graph approach (Christensen, Garrido, et al., 2023; Shi et al., 2025). It aims to maximize modularity (proportion of intra-connections vs. inter-connections across communities). An ideal partition (set of node community assignments) will therefore have more edges within communities and fewer edges between communities.

The Louvain algorithm (Blondel et al., 2008) optimizes modularity in two phases. The first, local moving of nodes, involves moving nodes to the community that yields that largest gain in the quality function. The second phase, aggregation, creates an aggregate network based on this partition. These steps are then repeated until the quality function (*Q*) converges to an optimum.

The intuition behind this algorithm is to form communities by maximizing links within a community and minimizing links from outside a community.

More formally, modularity (Q) is optimized as:

Equation 39

$$Q = \frac{1}{2m}\sum_{i=1}^{N}\sum_{j=1}^{N}\left[A_{ij} - \frac{k_i k_j}{2m}\right]\delta(c_i, c_j)$$

Where N is the total number of nodes, A_{ij} is the edge weight between nodes i and j, m is the sum of all edge weights, k is the node degree, and the function $\delta(c_i c_j)$ is 1 if the communities c_i for node i and c_j for node j are in the same cluster or zero if not. This formula selects communities that maximize node strength after subtracting for connections that would be expected to occur on the basis of chance.

There are two primary drawbacks to the Louvain algorithm. First, the resolution limit of modularity. This effect is defined by smaller communities being grouped together into larger communities—there is a resolution limit to the smallest recoverable community relative to the set. The second issue is that communities may become badly connected. This effect tends to occur when a node acting as a "bridge" (link between sets of nodes) becomes a member of a different community when a new iteration moves that node. These effects may not be salient in datasets common to psychology (Christensen, 2024).

Leiden

The Leiden algorithm (Traag et al., 2019) is similar to, though more complex than, the Louvain algorithm, but guarantees communities have strong intra-connections. As in the Louvain algorithm, Leiden community detection starts from a singleton partition wherein each node is a community. Nodes are aggregated to form larger communities. Nodes that are in their own community are moved to neighboring communities to maximize modularity. Critically, and different from Louvain, once a partition of communities is found, a new partition of communities within those previously-established communities is identified. Essentially, the algorithm checks for communities that are not internally well-connected, splitting fragmented communities into their own sub-communities. Sub-communities may later be merged to optimize modularity. As in Louvain modularity, communities are aggregated into super-nodes to create a smaller network.

The algorithm may optimize Q modularity as defined above, or other common metrics including the Constant Potts Model (Traag et al., 2011), where a desirable partition is recovered by minimizing the quantity $\mathcal{H}$ as defined:

Equation 40

$$\mathcal{H} = -\sum_{ij}(A_{ij}\omega_{ij} - \gamma)\delta(c_i, c_j)$$

Where the quantity $A_{ij}\omega_{ij}$ represents the edge weight between nodes, and γ is a resolution parameter. The Leiden algorithm effectively addresses the resolution limit of the Louvain algorithm, although careful selection of γ is required to ensure appropriate sensitivity to relatively small communities. It should also be noted that the Constant Potts Model was outperformed by Q modularity in preliminary testing, and therefore in this study, Q modularity is used. While the Leiden algorithm was developed to improve on a key limitation of the Louvain algorithm, empirical findings, especially on data resembling those in this study, are more equivocal (Christensen, 2024).

Walktrap

The Walktrap algorithm (Pons & Latapy, 2006) has been the most commonly-applied algorithm in the network psychometrics domain and is the default community detection algorithm in the *EGAnet* package. This initial selection by Golino & Epskamp (2017) of the Walktrap algorithm as the mode of community detection appears somewhat arbitrary. They note in that paper that the conditions under which the Walktrap algorithm performs well may not match those common to psychological data, and that other community detection algorithms should be tested. Despite this, subsequent work (Christensen, Garrido, et al., 2023) has confirmed the utility of the Walktrap algorithm.

The Walktrap algorithm uses the concept of random walks of a set length on a graph to produce a distance measure between nodes. Operating on the assumption that closer nodes form communities, this distance information can be used to identify those communities. The random walk must be long enough to gather such information but short enough to avoid reaching the stationary distribution that the probability of ending up on a given node is unrelated to the starting node and only depends on the final node's degree (number of connections). This distance between nodes *i* and *j* is computed as:

Equation 41

$$r_{ij} = \sqrt{\sum_{k=1}^{n} \frac{\left(P_{ik}^{t} - P_{jk}^{t}\right)^{2}}{d(k)}}$$

Where *d(k)* indicates the degree of node *k*, and P^t is the probability of the subscripted nodes reaching each other over a random walk of length *t*. This distance is equivalent to the Euclidean distance between the two probability distributions of vectors *I* and *j*.

The algorithm performs bottom-up hierarchical clustering of nodes into communities based this distance. Communities (including singletons) are merged by joining the closest communities into a new community, then updating the distances between adjacent communities. This repeats until all vertices have been joined into a single community, generating partitions along the way. Partition quality is usually assessed by maximizing modularity *Q*, which measures the proportion of edges within communities relative to the expected proportion if edges were placed randomly. A summary of these methods is below (Table 4).

Table 4. Summary of Community Detection Algorithms

Community Detection Algorithm	**Mechanism**	**Notes**
Louvain	Iteratively joins communities to create latent groups of nodes, usually by optimizing *Q* modularity until reaching a local maxima.	Has recently gained priority over Walktrap.

Leiden	Iteratively joins communities, usually by optimizing *Q* modularity until reaching a local maxima, but also checks for fragmented neighborhoods within larger communities.	Not resolution limited.
Walktrap	Generates pairwise node distances from random walks, then hierarchically clustered from those distances using Ward's method. A final partition is selected to maximize modularity.	The most common approach in EGA.

Out-of-Sample Prediction (fspe)

The most recent of these approaches is out-of-sample error prediction (J. M. B. Haslbeck & Van Bork, 2021), which slightly outperformed exploratory graph analysis and parallel analysis under the conditions tested by the authors. Notably, its performance was robust across conditions of number of factors, variables per factor, factor correlation, and sample size. In comparison, parallel analysis performed comparatively poorly when variables per factor was low and exploratory graph analysis was strongly affected by high factor correlations.

Out-of-sample prediction identifies the number of factors based on minimizing out-of-sample prediction error. This leverages a data science-informed approach, in which data are split into numerous train/test sets, where a factor model generated on the training data is then used to predict the test set. By generating models with different numbers of factors, it is possible to identify the optimal factor number by selecting the model that minimizes error in the test sets.

More specifically, this method fits factor models with 1 through p factors and computes the model-implied covariance matrix, which allows for p regression models, predicting a variable X_I from all other variables X_{-I}, which can then be used to compute a prediction error from X_i. These models are then used to compute an approximation of out-of-sample prediction error, which are averaged across cross-validation folds. The model that minimizes this prediction error is selected.

Present Studies

This work proposes two broad aims: first, to compare the performance of dimension reduction approaches on data specifically generated to simulate datasets collected during a lexical investigation and apply those findings to re-analyze a personality dataset; and second, to identify the performance of the dimension reduction techniques detailed above in data simulated to represent datasets more common to psychological research, as well as the conditions impacting their performance.

There will be two studies to accomplish the first aim, the first of which will simulate datasets meant to replicate the general structure of the data in Saucier & Goldberg (1996), systematically varying the parameters of the data generative process, then apply different dimension reduction approaches to these data, in order to identify which are most apt for the task. The second study will implement the identified approaches to that dataset from Saucier & Goldberg to attempt to replicate their findings. This dataset from Saucier & Goldberg was selected for both theoretical and pragmatic reasons. The study from which those data were derived extended a seminal study from Goldberg (1990) by including terms deemed more familiar to their undergraduate audience. It otherwise aimed to replicate past findings propounding the Big Five. Pragmatically, it was the best-cited work supporting the Big Five for which the data were readily available.

This implementation will extend past work assessing methodological convergence around a model of personality by employing methods that are both empirically state-of-the-art and conceptually different than those past methods.

While an interesting endeavor, these two studies would have limited insight for the broader factor analytic literature, given the characteristics of the dataset tested. Thus, the secondary aim of this dissertation is to identify the optimal approach to dimension detection in conditions more common to psychological survey-based data, as well as provide a nuanced overview of conditions that may indicate a different approach. This aim will be similarly accomplished by means of a simulation study, in which datasets will be generated by combinations of different levels of variables representing those conditions. Consequently, these findings should provide clarity to best practices in designing a study in which factor analysis is expected. Note that this study (Study 1) is presented first, as it provides a background to the more esoteric methods used in estimating networks among larger sets of data, which will be employed in the personality-related studies.

Chapter 2: Study 1

Introduction

The goal of this study is to compare the performance of modern factor analytic methods on data with a known factor structure simulated to mimic psychological survey data. This will identify the optimal approach or approaches and their interaction with conditions of those data.

Identifying the number of factors in a dataset is essentially a branch of unsupervised learning—a widely studied branch of computer science involving determination of group membership of data without pre-existing labels. However, bringing computer science approaches to bear in this endeavor is a relatively recent advance in the psychological literature, which previously relied on eigenvariate methods as the main method of factor identification. This is an area of active research and has brought incremental improvement to the issue of factor number selection (J. M. B. Haslbeck & Van Bork, 2021). However, given the rapidly-advancing knowledge base and the relatively narrower common use case for factor detection in psychological data as compared to applied math or computer science, there are open questions around the optimal methods given the characteristics of the data involved. Any mathematical means of identifying factors will have its own nuances affecting the relationship between data and solution. This study speaks to those nuances.

Specifically, I compare the dimension detection approaches of exploratory graph analysis using combinations of different community detection algorithms (Leiden, Louvain, and Walktrap) and network estimation approaches (Log, Atan, Lasso, Adaptive Lasso, Fisher's R-to-Z transformed partial correlation), as well as parallel analysis, and out-of-sample prediction (J. M. B. Haslbeck & Van Bork, 2021) in their ability to accurately recover the number of factors across datasets with varied conditions.

A critical aspect of this study is to compare the performance of dimension reduction approaches across conditions that may be more reflective of psychological measurement than their respective simulation studies often assume. To that end, I simulated survey data by generating datasets of factorial data, varying the following parameters: factor loadings, number of factors, items per factor, factor correlations, number of response options, proportion of variables exhibiting non-linearity in the item-factor relationship, sample size, and items per factor imbalance. These datasets were submitted to dimension reduction by state-of-the-art approaches, including parallel analysis, out-of-sample factor prediction, and exploratory graph analysis.

This allowed for comparison of performance across conditions and interactions between conditions. Importantly, even if no single approach dominated, these findings were likely to guide researchers in identifying an optimal approach for particular use cases.

Methods

Data-Generating Mechanism

To assess performance of these various algorithms, datasets were simulated using a Monte Carlo design in which eight parameters in the data generative process were systematically varied with a similar approach to past works in this vein (Garrido et al., 2016; H. Golino et al., 2020). These parameters (Table 5) include factor loadings, number of factors, items per factor, factor correlations, number of response options, proportion of variables exhibiting non-linearity in the item-factor relationship, sample size, and items per factor imbalance. The *latentFactoR* package (Christensen, Nieto Canaveras, et al., 2023) was used to generate these data. This package implements a common factor-based data generating model. Note that this does not bias the preferred solution away from a network-based method, as factors and network communities are statistically equivalent, though they imply a different theoretical genesis. Further, network-based methods have been empirically preferred using this approach (H. Golino et al., 2020; H. Golino & Christensen, 2024).

Number of factors

Structures ranging from one to five factors were simulated. Critically, this included the case of uni-dimensionality, for which some dimension detection algorithms have exhibited inaccuracy (H. Golino et al., 2020). Further, given that the median number of first-order factors in the psychology literature is three (Jackson et al., 2009), this simulation tested both for conditions not only common to psychology and for cases on both sides of the median.

Factor loadings

Factor loadings were simulated at levels randomly drawn from three ranges: .30-.50, .45-.65, and .60-.80. These ranges, respectively, represent poor, good, and excellent factor loadings (Comrey, 1978); again, a range of results found in the psychological literature.

Items per factor

Items per factor included 3, 5, and 8. Three items is the minimum for factor identification (Anderson & Rubin, 1956), whereas five is a more common number that allows for an overidentified model, and eight represents a number of items per factor that would be high though not previously unseen (Velicer, 1976).

Items per factor Imbalance

Items per factor had a second condition in which they were allowed to vary from 3-8, producing factors with imbalanced numbers of items. Dimension detection algorithms may perform differentially based on this condition; it is well known, for instance, that the k-means algorithm performs sub-optimally when cluster sizes are not similarly proportioned.

Factor correlations

Factor correlations were simulated at levels of .00 (orthogonal), .30 (medium correlation level), .50 (large correlation level), and .70 (very large correlation level). Factor correlations introduce much of the difficulty in identifying underlying dimensions, as they produce strong interrelationships between constructs that researchers aim to distinguish between. Though a large correlation between factors does not preclude them having distinct meanings (and thus reasonable targets of dimension reduction), correlations in excess of .70 may introduce multicollinearity issues making them inappropriate for measurement models (Shao et al., 2022).

Number of response options

Number of response options were manipulated to reflect common survey conditions which frequently use dichotomous or polytomous data. Validating dimension reduction approaches for psychological data on simulated continuous data has been the norm (H. Golino et al., 2020; H. F. Golino & Epskamp, 2017; J. M. B. Haslbeck & Van Bork, 2021)–despite dimension reduction approaches being less accurate when simulated data are non-continuous–to the extent of possibly changing ordering of performance (when comparing multiple approaches) across continuous vs. non-continuous conditions (J. M. B. Haslbeck & Van Bork, 2021).

In psychology, five-point Likert-type responses are common (Sullivan & Artino, 2013), though some researchers suggest using six or more response options in order to more safely treat variables as continuous (Wakita et al., 2012). Therefore, we used three common item response formats of two, five, and seven-option items. The association between dichotomous variables was calculated using tetrachoric correlations, and polychoric correlations were computed for the other conditions.

Non-linearity

Factor analytic methods hold the assumption of linearity of the factor-indicator relationship, an assumption which may be violated in practice. This may occur when changing levels of the latent construct produce diminishing or increasing differences of the observed variables. Bauer (2005) cites an example of observers having greater difficulty distinguishing between low and moderate levels of aggression than moderate and high aggression. Ceiling effects are similarly problematic.

There are innumerable possible non-linear relationships between an item response and factor score. Example forms of these functions are sigmoidal, quadratic, or exponential (Bauer, 2005). This study considers a quadratic function of the form:

$$Equation\ A\colon \chi_i = \tau + \lambda\xi_i + \omega\xi_i^2 + \varepsilon_i$$

where ω designates the magnitude of the quadratic effect. In this study, we used a moderately sized effect, ω=.08 (Bauer, 2005). This function is non-symmetric around a factor level of zero. These data were simulated under conditions either without this consideration, or where 50% of variables (rounded up) were transformed accordingly.

Sample Size

Datasets with 200, 400, 600 and 1000 observations were tested. These sample sizes account for the need of a larger sample size when using tetrachoric correlation (Timmerman & Lorenzo-Seva, 2011). When data are well-conditioned (high factor loadings, few factors, and a high number of variables), exploratory factor analysis may produce reliable results for *N*<50 (De Winter & Dodou, 2016), although more commonly recommended minimum sample sizes range from 200-1000 (Comrey & Lee, 2013).

Non-varied parameters

More additional steps were taken in simulating these data to generate realistic response datasets. Cross-loadings were randomly drawn from a normal distribution $N(0, .05)$ for all items. Skewness will also be introduced for each item as a random uniform distribution of -2 to 2 in increments of .50.

Table 5. Monte Carlo data generation parameters

Condition	**Levels**
Number of factors	1,2,3,4,5
Factor loadings	0.30-.50
	0.45-.65
	0.60-0.80
Items per factor	3,5,8
Factor correlations	.00, .30, .50, .70
Number of response options	2, 5, 7
Items per factor imbalance	N/A or range from 3-8
Non-linearity	0% or 50% of items (rounded up)
Sample sizes	200, 400, 600, 1000

The set and levels of conditions allowed for a full factorial design: 5x3x3x4x3x2x2x4, or 8,640 total combinations. Each combination was simulated 100 times, for a total of 86,400 data matrices.

Regularization Network Estimation

The regularization approaches included were GLASSO, Atan, Adaptive Lasso, Log penalty and Fisher Z-transformed confidence intervals. To select a single network from all but the Fisher-Z transformed networks, different information criteria were used. These include BIC, eBIC, GIC_3, and GIC_4. Treatments of regularization and information criteria can be found in the introduction to this dissertation.

Dimension Detection Approaches

Dimension detection approaches applied to regularized networks (i.e., community detection) were the Leiden, Louvain, and walktrap algorithms. Dimension detection approaches applied to non-regularized data were out-of-sample-prediction (fspe), and parallel analysis (both principal components and factors; PA). To estimate clusters from fspe and PA, different rotations were used, including geominQ, oblimin, varimax, and the unrotated components. In the factor analytic approaches, variables clustered based on their absolute highest factor loading.

Performance Measures

To assess performance of the dimensionality methods, four criteria were evaluated: percentage of correct factors (PC or Accuracy), mean absolute error (MAE), mean bias error (MBE), and adjusted Rand index (ARI). Percentage of correct factors (Equation 42; N_{11} indicates observations where the estimated and true factor numbers are the same) will be computed as the count of correct factor numbers rendered divided by the total count of simulated data matrices. It thus ranges from 0% (complete inaccuracy) to 100% (perfect accuracy).

Equation 42

$$Accuracy = \frac{N_{11}}{n}$$

Mean absolute error (Equation 43) is computed as the absolute (magnitude of the) difference between the number of factors identified and the empirically-correct number of factors for that data matrix divided by the total number of simulated data matrices. A value of zero on

MAE indicates perfect accuracy, while higher values indicate larger routine departures from accuracy.

Equation 43

$$MAE = \frac{\sum_{i=1}^{n} |y_i - x_i|}{n}$$

Mean bias error (Equation 44) is calculated similarly to the mean absolute error but does not use the absolute value of the difference. It is theoretically unbounded, with positive values indicating overfactoring (i.e., extracting too many factors) and negative values indicating underfactoring (i.e., extracting too few factors).

Equation 44

$$MBE = \frac{\sum_{i=1}^{n} y_i - x_i}{n}$$

Comparison of factor clustering solutions will use the Adjusted Rand Index. Adjusted Rand Index (Equation 46; Meila, 2016), and the unadjusted Rand Index (Equation 45) are widely-used metrics of cluster similarity. The un-adjusted Rand index simply measures the fraction of points on which both clustering solutions agree (N_{11}) or disagree (N_{00}). The adjusted Rand index corrects for chance. In its adjusted form, its expected value is zero, while its maximum is 1. In this case, clusters are edges found in the regularized solutions compared to the ground truth of edges within factorial blocks.

Equation 45

$$RI(C, C') = \frac{N_{00} + N_{11}}{n(n-1)/2}$$

Equation 46

$$ARI(C, C') = \frac{R(C, C') - E[R]}{1 - E[R\}}$$

As numerous datasets were generated under the same combination of conditions, mean and standard deviations were assessed for each algorithmic approach under each set of conditions. This facilitated comparison of the optimal approach per set of conditions.

Analyses of variance (ANOVA) were conducted to examine the effects of combinations of conditions that impacted accuracy. These analyses employed MAE, MBE, PC, and ARI from the different dimension reduction approaches, with the different factor conditions serving as the independent factors. Partial eta squared η^2 was used as the measure of effect size to assess main effects and interactions of the independent variables.

Computational Aspects

All data generation and analyses were performed using R Version 4.4.1 (R Core Team, 2022). Data generation was performed using the *latentFactoR* package (version 0.0.6; Christensen, Nieto Canaveras, et al., 2023). The EBICGLASSO method was run with the *EGAnet* package (version 2.0.7; H. Golino & Christensen, 2024). All other regularization were run using the *GGMncv* package (version 2.1.1; D. Williams, 2020). Out-of-sample prediction (*fspe*) was performed with the *fspe* package (version 0.1.2; J. Haslbeck, 2023). Walktrap, Leiden, and Louvain community detection algorithms were run with the *igraph* package (version 2.1.1; Csárdi et al., 2024). Parallel analysis, FA, and PCA (including rotations) were implemented from the *psych* package (version 2.4.6; Revelle, 2024). Adjusted Rand Index was calculated using the *mclust* package (version 6.1.1; Scrucca et al., 2023). This code, and data to reproduce the study and its analyses, were made available at the Open Science Framework (https://osf.io/36wn7/).

Results

The performance of each dimension reduction method was heavily dependent on the characteristics of the data being analyzed. This finding is not novel but serves to highlight that the true dimensionality of data is easily obscured.

Across all methods, higher-order interaction effects were minimal (see heatmaps in appendices; Table 28-Table 47). Results by method collapsed across all conditions are presented below (Table 6). Note that factor estimates from fspe and parallel analysis do not have a value for ARI, as they do not inherently produce a clustering but instead can be used to produce a rotation that has a clustering. By similar logic, Accuracy, MAE, and MBE are omitted for the rotational derivations of fspe and parallel analysis (both principal components and principal factors), as their factor estimate is derived from the same non-rotated source and is therefore redundant.

Table 6. Average performance across all conditions, sorted by ARI

Algorithmic Approach	ARI	Accuracy	MAE	MBE	Over/Under Factored?
EGAnet	.83 [.83, .83]	.8 [.8, .8]	0.31 [0.31, 0.31]	-0.17 [-0.17, -0.17]	Under
PA_FA		.66 [.66, .66]	0.76 [0.76, 0.76]	0.32 [0.32, 0.33]	Over
PA_FA_geominQ	.77 [.77, .77]				N/A
PA_FA_none	.32 [.31, .32]				N/A
PA_FA_oblimin	.76 [.76, .76]				N/A
PA_FA_varimax	.77 [.77, .77]				N/A
PA_PC		.71 [.71, .71]	0.54 [0.54, 0.54]	-0.28 [-0.29, -0.28]	Under
PA_PC_geominQ	.79 [.79, .79]				N/A
PA_PC_none	.37 [.37, .37]				N/A
PA_PC_oblimin	.78 [.78, .79]				N/A
PA_PC_varimax	.79 [.79, .79]				N/A
R2Z_leiden	.74 [.74, .74]	.74 [.73, .74]	0.30 [0.30, 0.30]	-0.09 [-0.09, -0.08]	Under
R2Z_louvain	.74 [.74, .74]	.74 [.74, .74]	0.30 [0.30, 0.30]	-0.08 [-0.08, -0.08]	Under
R2Z_walktrap	.69 [.69, .69]	.64 [.64, .64]	0.64 [0.64, 0.65]	-0.57 [-0.57, -0.57]	Under
fspe		.73 [.73, .73]	0.46 [0.46, 0.46]	-0.34 [-0.35, -0.34]	Under
fspe_geominQ	.79 [.79, .79]				N/A
fspe_none	.33 [.33, .33]				N/A
fspe_oblimin	.79 [.79, .79]				N/A
fspe_varimax	.79 [.79, .79]				N/A
leiden_adapt_bic	.77 [.77, .77]	.77 [.77, .77]	0.26 [0.26, 0.27]	0.06 [0.06, 0.06]	Over

leiden_adapt_ebic	.73 [.73, .73]	.73 [.73, .73]	0.45 [0.45, 0.46]	-0.17 [-0.17, -0.17]	Under
leiden_adapt_gic_3	.78 [.78, .78]	.77 [.77, .77]	0.27 [0.27, 0.28]	0.05 [0.05, 0.06]	Over
leiden_adapt_gic_4	.77 [.77, .77]	.77 [.77, .77]	0.32 [0.32, 0.32]	-0.01 [-0.01, -0.01]	Under
leiden_atan_bic	.75 [.74, .75]	.74 [.74, .74]	0.30 [0.30, 0.30]	0.12 [0.12, 0.12]	Over
leiden_atan_ebic	.74 [.74, .74]	.73 [.73, .73]	0.35 [0.34, 0.35]	0.18 [0.18, 0.18]	Over
leiden_atan_gic_3	.76 [.76, .76]	.75 [.75, .75]	0.29 [0.29, 0.29]	0.13 [0.12, 0.13]	Over
leiden_atan_gic_4	.76 [.76, .76]	.75 [.75, .76]	0.30 [0.30, 0.30]	0.16 [0.16, 0.16]	Over
leiden_lasso_bic	.77 [.77, .77]	.76 [.76, .76]	0.28 [0.27, 0.28]	0.01 [0.01, 0.01]	Over
leiden_lasso_ebic	.73 [.73, .73]	.73 [.73, .73]	0.43 [0.43, 0.43]	-0.18 [-0.18, -0.18]	Under
leiden_lasso_gic_3	.77 [.77, .77]	.76 [.76, .76]	0.28 [0.28, 0.28]	0.01 [0, 0.01]	Over
leiden_lasso_gic_4	.77 [.77, .77]	.76 [.76, .76]	0.31 [0.3, 0.31]	-0.03 [-0.03, -0.03]	Under
leiden_log_bic	.76 [.76, .76]	.76 [.76, .76]	0.28 [0.28, 0.28]	0.09 [0.09, 0.1]	Over
leiden_log_ebic	.73 [.73, .73]	.72 [.72, .72]	0.47 [0.47, 0.47]	-0.12 [-0.12, -0.12]	Under
leiden_log_gic_3	.77 [.77, .77]	.77 [.77, .77]	0.28 [0.28, 0.28]	0.08 [0.08, 0.08]	Over
leiden_log_gic_4	.77 [.77, .77]	.76 [.76, .76]	0.33 [0.32, 0.33]	0.03 [0.03, 0.04]	Over
louvain_adapt_bic	.77 [.77, .77]	.77 [.77, .77]	0.27 [0.27, 0.27]	0.07 [0.07, 0.07]	Over
louvain_adapt_ebic	.73 [.73, .73]	.73 [.73, .73]	0.45 [0.45, 0.46]	-0.17 [-0.17, -0.17]	Under
louvain_adapt_gic_3	.77 [.77, .77]	.77 [.77, .77]	0.28 [0.27, 0.28]	0.06 [0.06, 0.06]	Over
louvain_adapt_gic_4	.77 [.77, .77]	.77 [.77, .77]	0.32 [0.32, 0.32]	-0.01 [-0.01, 0]	Under
louvain_atan_bic	.74 [.74, .74]	.74 [.74, .74]	0.30 [0.30, 0.30]	0.12 [0.12, 0.13]	Over
louvain_atan_ebic	.73 [.73, .74]	.73 [.72, .73]	0.35 [0.35, 0.35]	0.18 [0.18, 0.18]	Over
louvain_atan_gic_3	.75 [.75, .75]	.75 [.75, .75]	0.29 [0.29, 0.29]	0.13 [0.13, 0.13]	Over
louvain_atan_gic_4	.75 [.75, .76]	.75 [.75, .75]	0.31 [0.31, 0.31]	0.16 [0.16, 0.16]	Over
louvain_lasso_bic	.77 [.76, .77]	.76 [.76, .76]	0.28 [0.28, 0.28]	0.01 [0.01, 0.01]	Over
louvain_lasso_ebic	.73 [.73, .73]	.73 [.73, .73]	0.43 [0.42, 0.43]	-0.18 [-0.18, -0.18]	Under
louvain_lasso_gic_3	.76 [.76, .76]	.76 [.76, .76]	0.29 [0.29, 0.29]	0.01 [0.01, 0.01]	Over
louvain_lasso_gic_4	.77 [.76, .77]	.76 [.76, .76]	0.31 [0.31, 0.31]	-0.03 [-0.03, -0.03]	Under
louvain_log_bic	.76 [.76, .76]	.76 [.76, .76]	0.28 [0.28, 0.29]	0.10 [0.10, 0.10]	Over
louvain_log_ebic	.72 [.72, .73]	.72 [.72, .72]	0.47 [0.47, 0.47]	-0.12 [-0.12, -0.12]	Under
louvain_log_gic_3	.76 [.76, .77]	.77 [.76, .77]	0.28 [0.28, 0.29]	0.09 [0.09, 0.09]	Over
louvain_log_gic_4	.76 [.76, .76]	.76 [.76, .76]	0.33 [0.33, 0.33]	0.03 [0.03, 0.04]	Over
walktrap_adapt_bic	.78 [.78, .78]	.77 [.76, .77]	0.30 [0.30, 0.30]	-0.03 [-0.03, -0.03]	Under
walktrap_adapt_ebic	.75 [.75, .75]	.74 [.74, .74]	0.45 [0.45, 0.45]	-0.21 [-0.21, -0.21]	Under
walktrap_adapt_gic_3	.78 [.78, .78]	.77 [.77, .77]	0.31 [0.3, 0.31]	-0.03 [-0.03, -0.03]	Under
walktrap_adapt_gic_4	.79 [.78, .79]	.77 [.77, .77]	0.33 [0.33, 0.34]	-0.07 [-0.07, -0.07]	Under
walktrap_atan_bic	.75 [.75, .75]	.74 [.74, .74]	0.33 [0.33, 0.33]	0.06 [0.06, 0.06]	Over
walktrap_atan_ebic	.75 [.75, .75]	.73 [.73, .73]	0.37 [0.36, 0.37]	0.18 [0.18, 0.18]	Over
walktrap_atan_gic_3	.76 [.76, .76]	.75 [.75, .75]	0.32 [0.32, 0.33]	0.08 [0.07, 0.08]	Over
walktrap_atan_gic_4	.77 [.77, .77]	.75 [.75, .76]	0.33 [0.33, 0.33]	0.14 [0.13, 0.14]	Over
walktrap_lasso_bic	.77 [.77, .77]	.76 [.76, .76]	0.34 [0.33, 0.34]	-0.17 [-0.17, -0.16]	Under
walktrap_lasso_ebic	.75 [.74, .75]	.74 [.74, .74]	0.43 [0.43, 0.43]	-0.26 [-0.26, -0.26]	Under
walktrap_lasso_gic_3	.77 [.77, .77]	.76 [.76, .76]	0.34 [0.33, 0.34]	-0.16 [-0.16, -0.16]	Under
walktrap_lasso_gic_4	.78 [.78, .78]	.77 [.77, .77]	0.33 [0.33, 0.33]	-0.15 [-0.15, -0.15]	Under
walktrap_log_bic	.77 [.77, .77]	.76 [.76, .76]	0.31 [0.30, 0.31]	0.01 [0.01, 0.01]	Over
walktrap_log_ebic	.74 [.74, .74]	.73 [.73, .74]	0.47 [0.46, 0.47]	-0.15 [-0.15, -0.14]	Under
walktrap_log_gic_3	.78 [.78, .78]	.76 [.76, .76]	0.31 [0.31, 0.31]	0.02 [0.01, 0.02]	Over
walktrap_log_gic_4	.78 [.78, .78]	.77 [.77, .77]	0.34 [0.34, 0.34]	-0.01 [-0.01, -0.01]	Under

Note 1. 95% Confidence Intervals of the mean are presented in brackets

Note 2. Walktrap, Louvain, Leiden indicate which community detection algorithm was used. Adapt, Atan, Lasso, Log, and R2Z (Fisher's Z-transformed confidence intervals) indicate how the network was regularized. Ebic, bic, GIC_3, and GIC_4 refer to which information criterion was used (NA for Fisher's Z-transformed confidence intervals).

PA indicates that parallel analysis was used; FA or PC indicates whether principal components or factors were used. GeominQ, Oblimin, Varimax, or None refers to the rotation type.

Figures comparing performance across factor levels clearly demonstrate the overall strong performance of most methods across multidimensional cases. It is also notable that multidimensional constructs are much easier to detect than unidimensional ones (Figure 2, Figure 3, Figure 4, Figure 5, Figure 6). Again, this observation is not novel, having motivated the multi-stage design of the *EGAnet* approach, which, not coincidentally, was overall the most successful approach, largely due to its comparative success in the unidimensional condition.

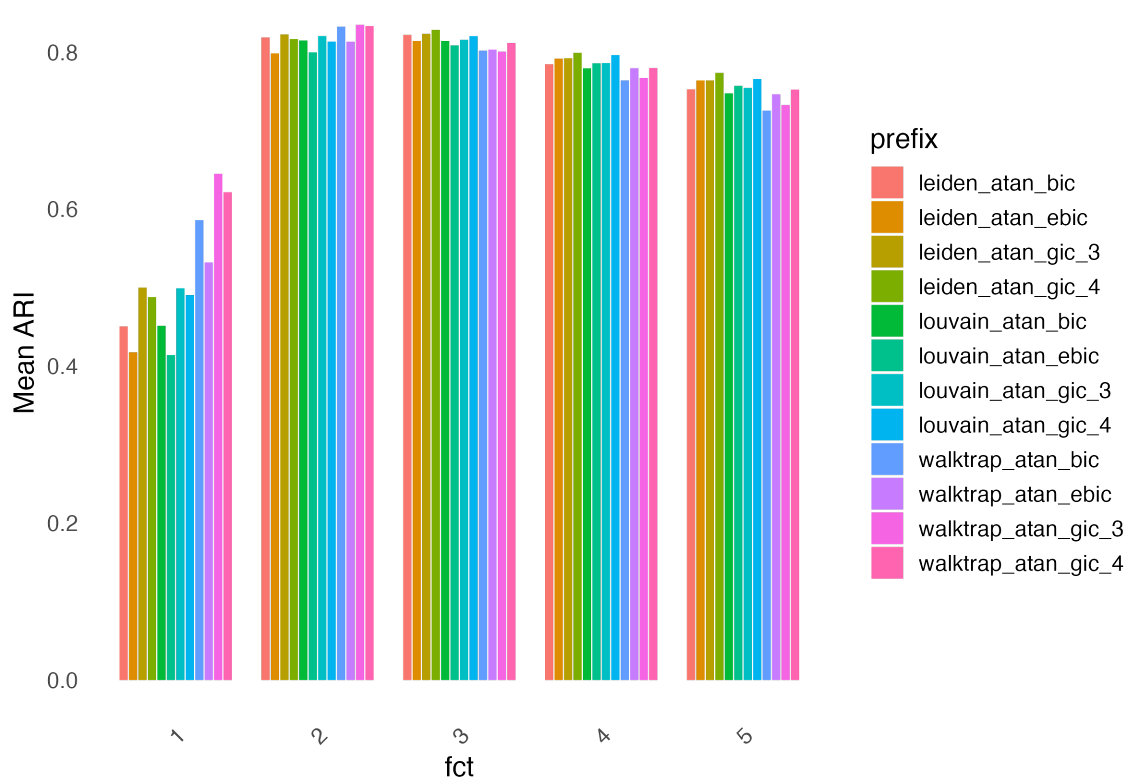


Figure 2. ARI by Factor Level (Part 1)

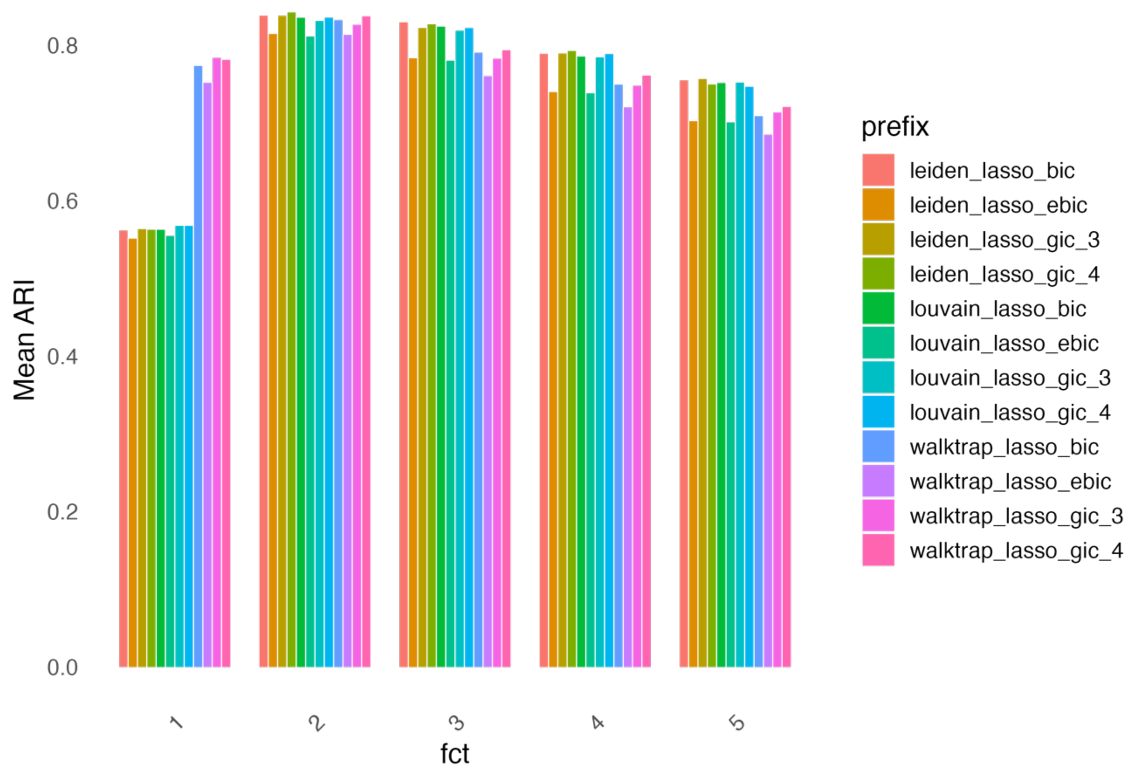


Figure 3. ARI by Factor Level (Part 2)

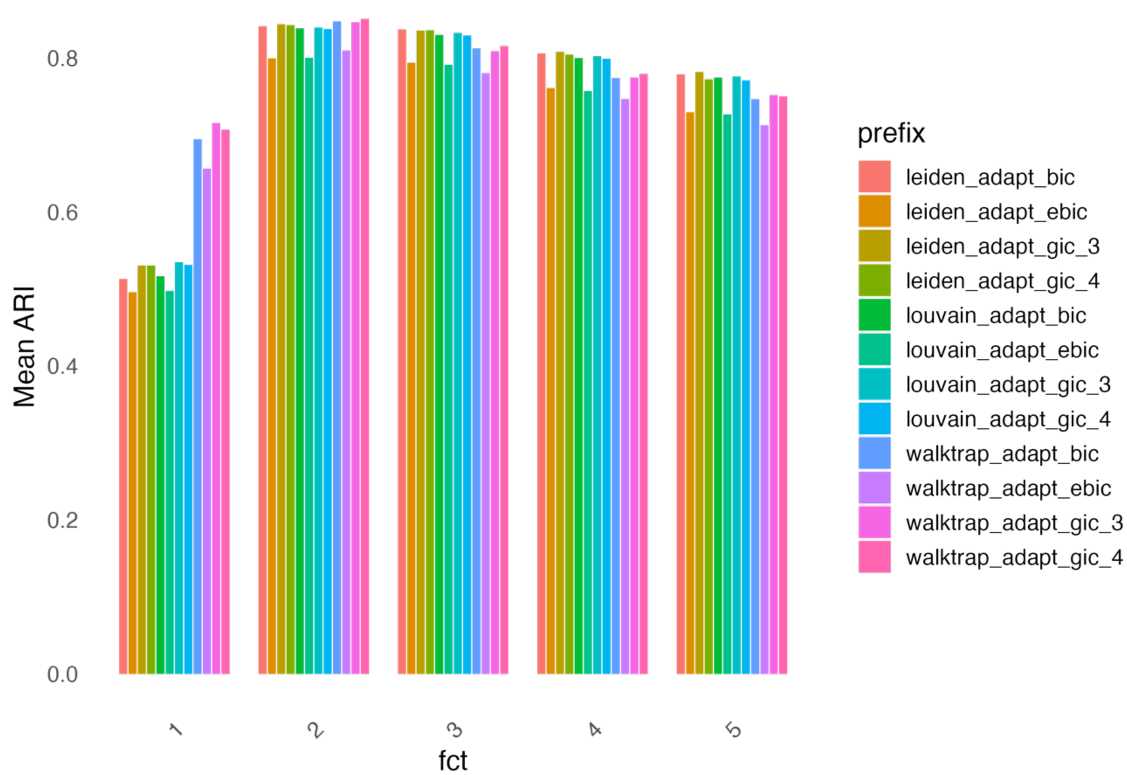


Figure 4. ARI by Factor Level (Part 3)

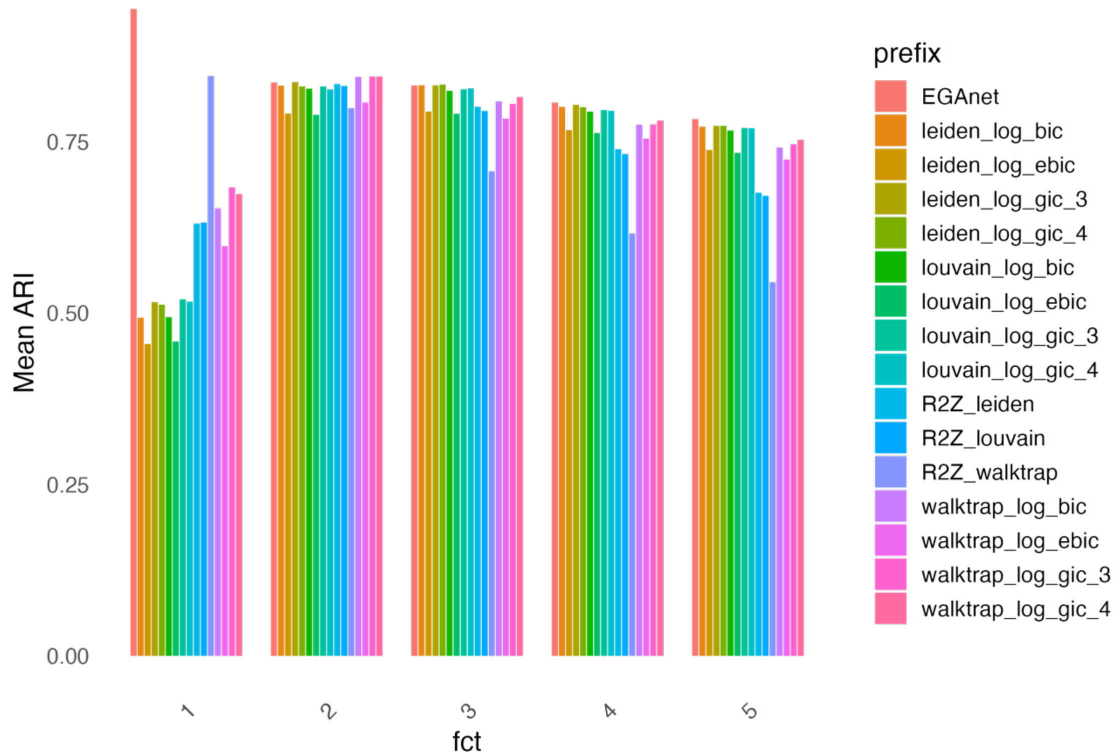


Figure 5. ARI by Factor Level (Part 4)

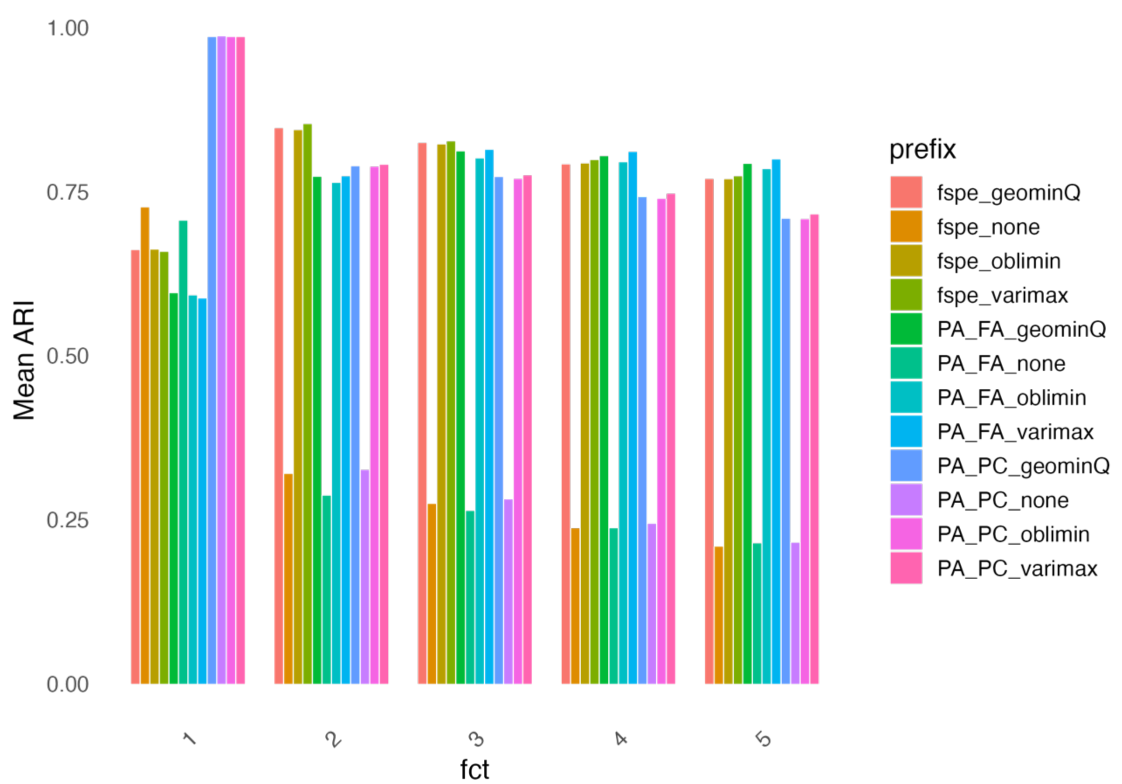


Figure 6. ARI by Factor Level (Part 5)

Overall, all methods were reasonably effective at producing valid clusterings, as assessed by ARI. In terms of accuracy, the greatest distinction is the poor performance from using unrotated components extracted from *fspe*, principal components (PC), and factors (FA). ARI otherwise ranged from 0.833 (*EGAnet*) to 0.692 (Walktrap on R-to-Z "regularization"). Despite the weak performance of the Walktrap algorithm on the R-to-Z "regularization" scheme, that same method was highly effective at identifying one- and two-factor solutions, at the cost of being inaccurate for higher-dimensional conditions.

Of the variables manipulated in data generation, the most impactful were sample size (Figure 7, Figure 8, Figure 9, Figure 10, Figure 11), factor correlation (Figure 12, Figure 13, Figure 14, Figure 15, Figure 16), and factor loading (Figure 17, Figure 18, Figure 19, Figure 20, Figure 21). As factor loading and sample size increased, performance improved. However, as factors became increasingly correlated, performance decreased.

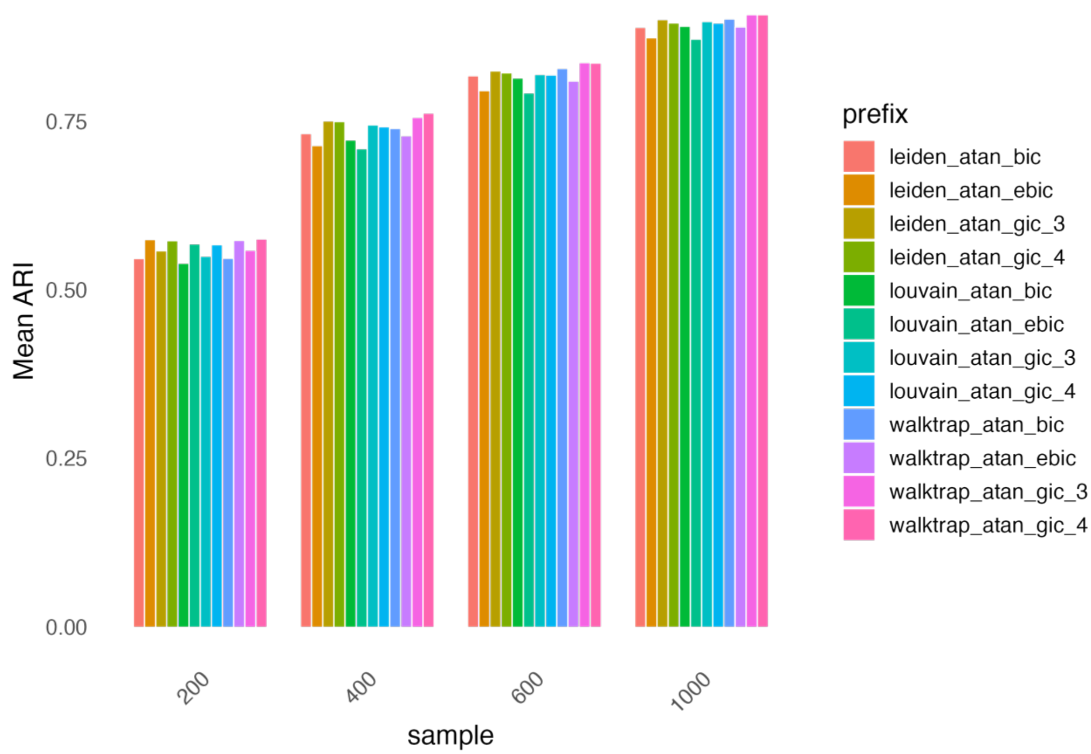


Figure 7. ARI by Sample Size (Part 1)

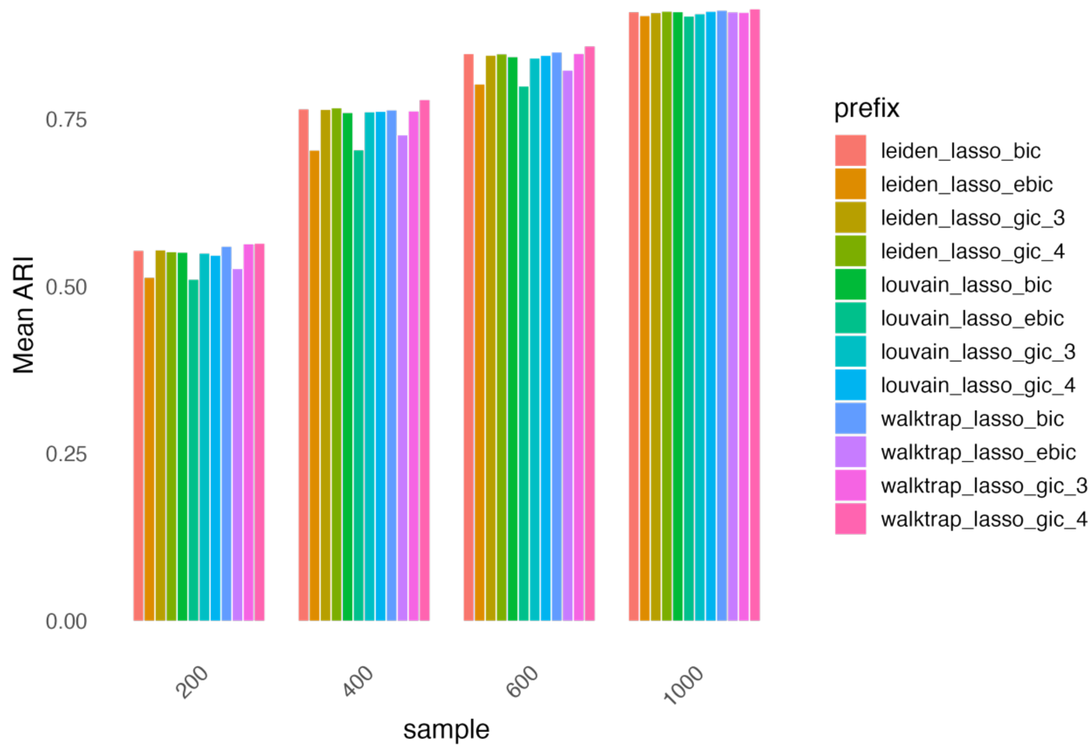


Figure 8. ARI by Sample Size (Part 2)

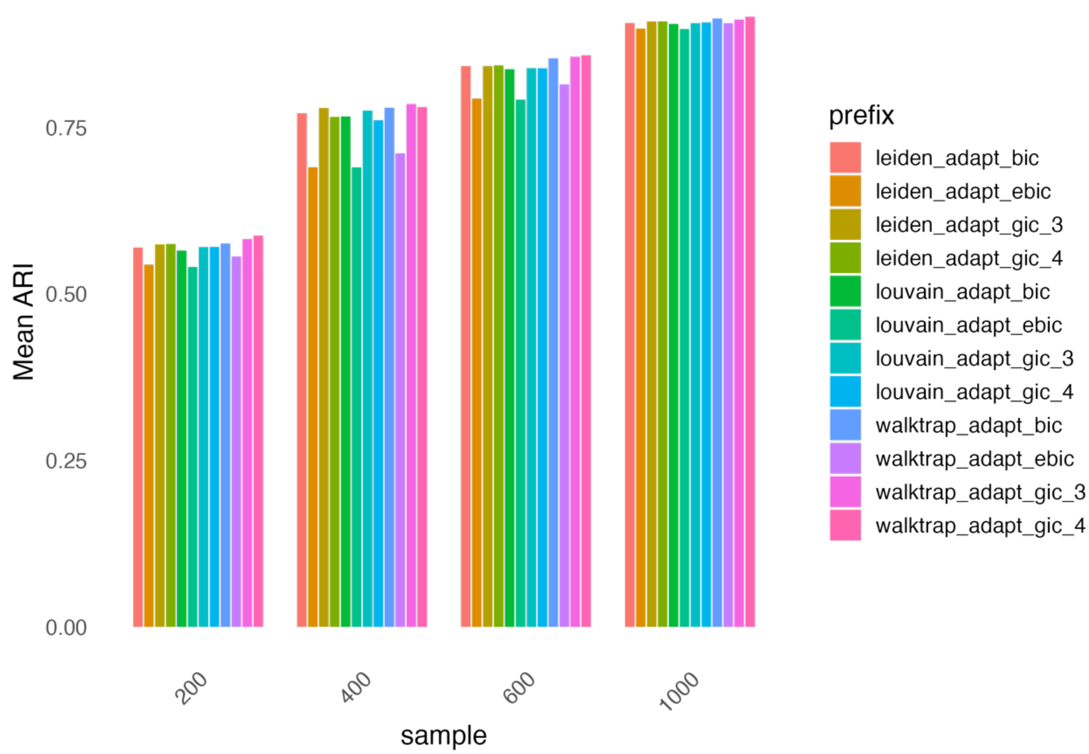


Figure 9. ARI by Sample Size (Part 3)

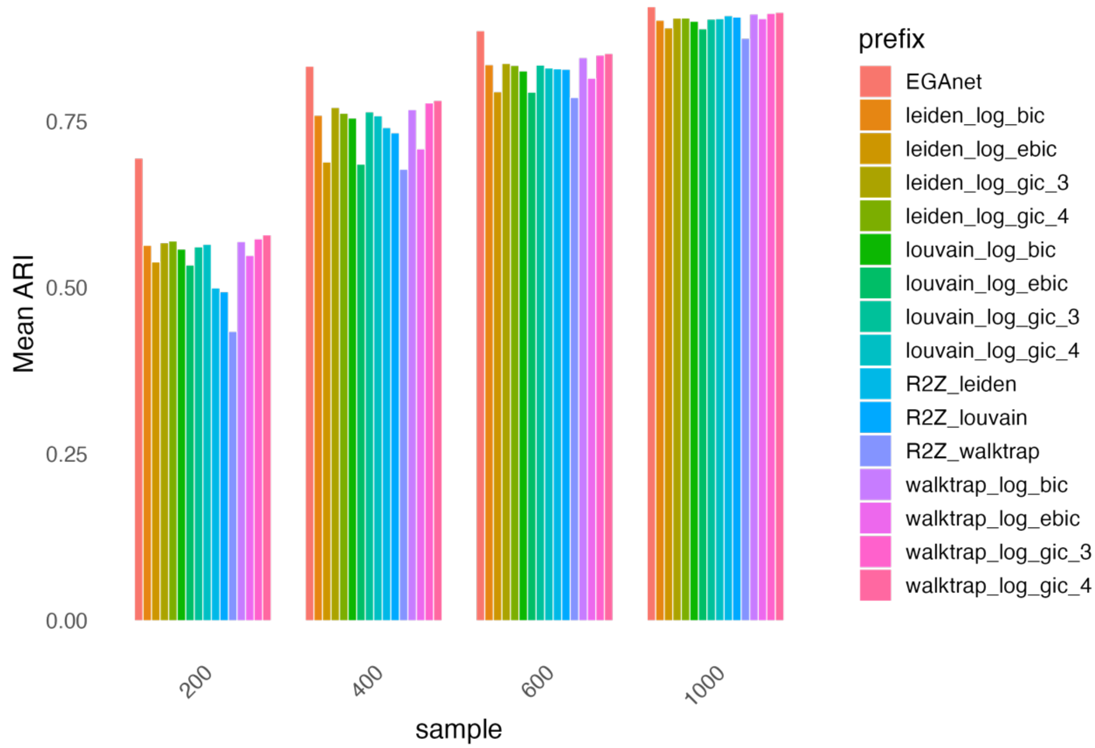


Figure 10. ARI by Sample Size (Part 4

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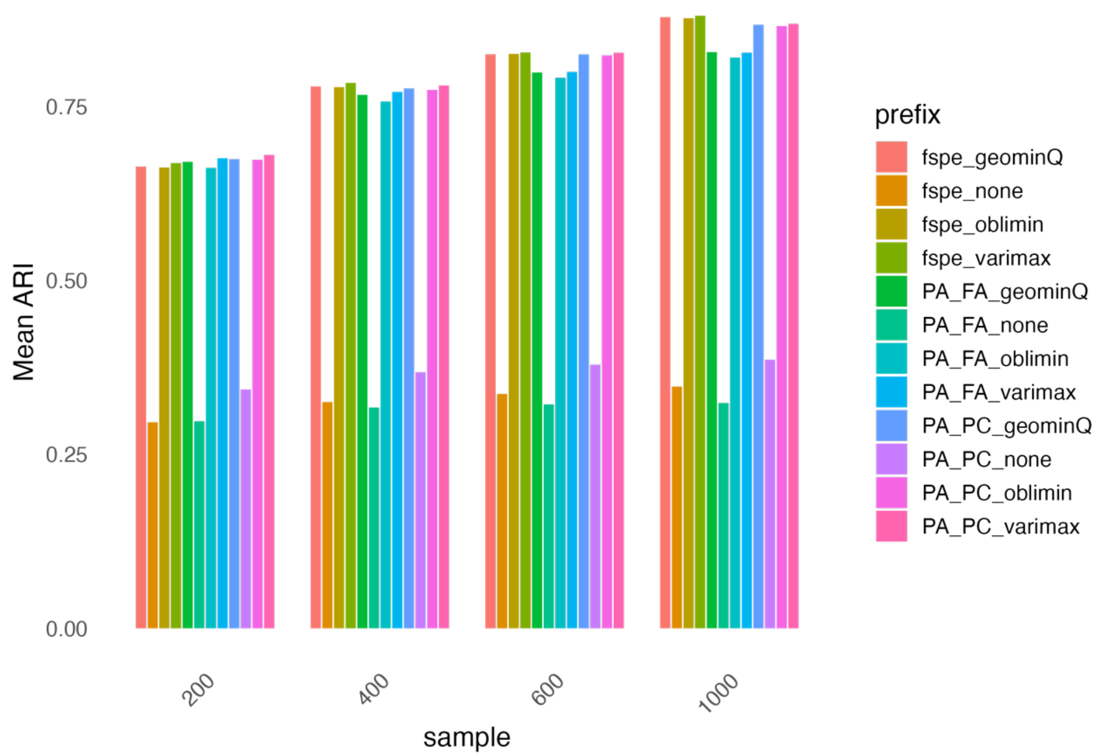

Figure 11. ARI by Sample Size (Part 5)

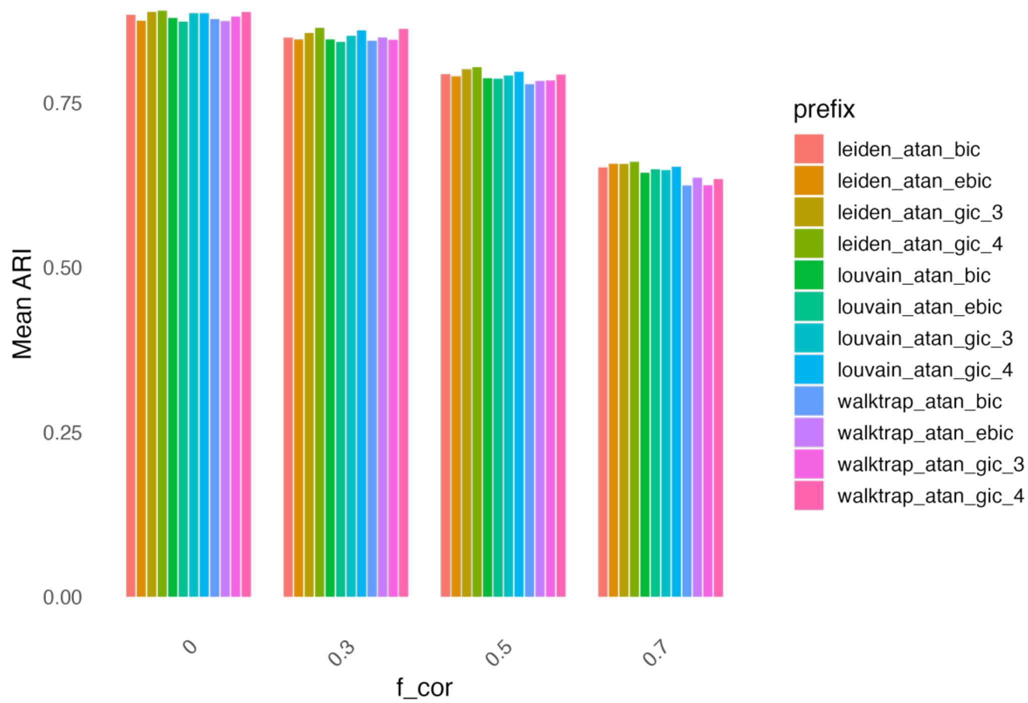

Figure 12. ARI by Factor Correlation (Part 1)

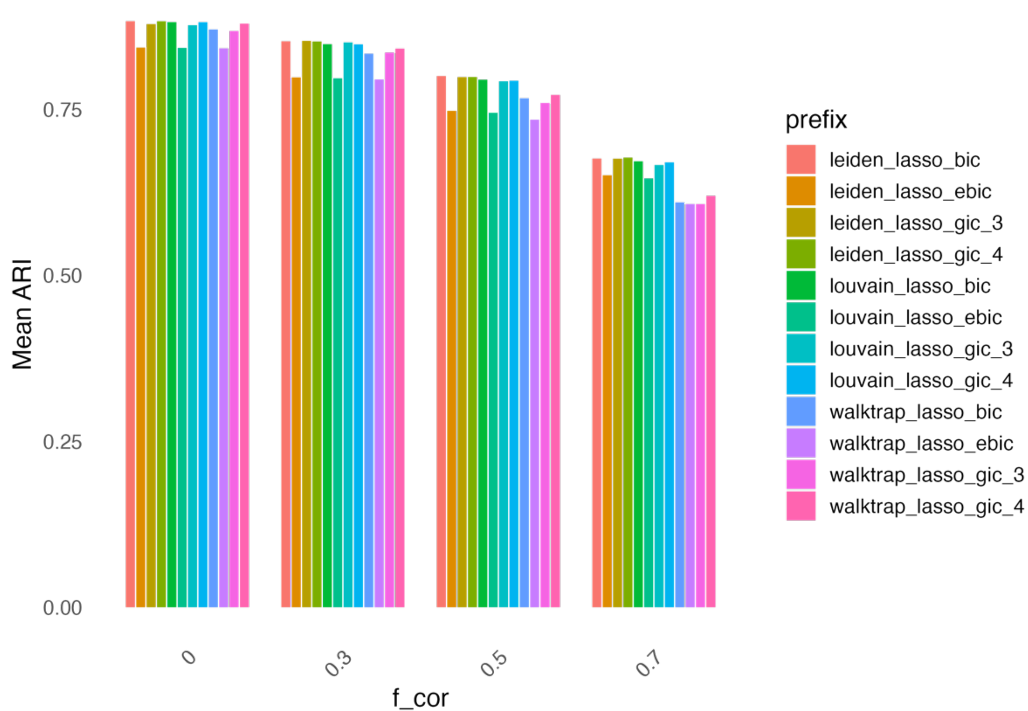

Figure 13. ARI by Factor Correlation (Part 2)

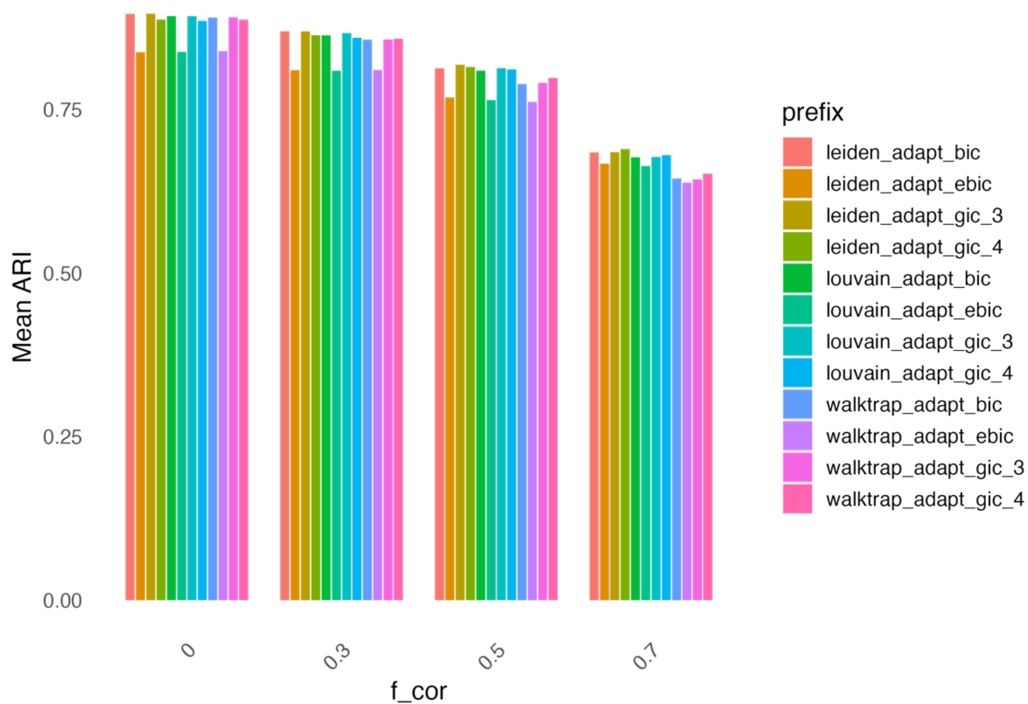

Figure 14. ARI by Factor Correlation (Part 3)

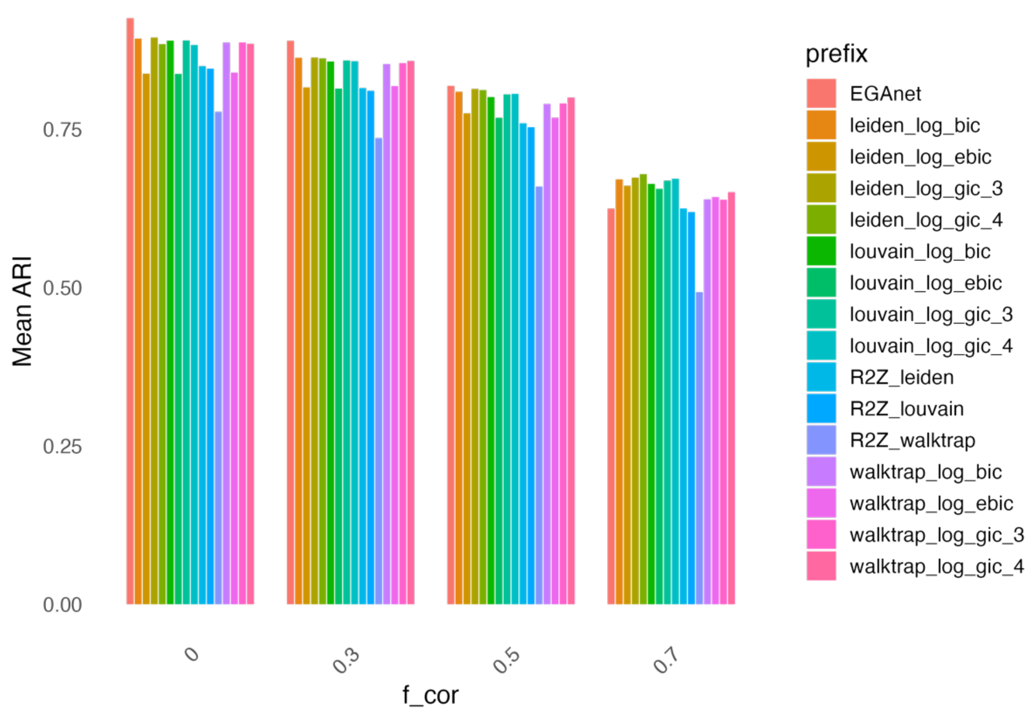

Figure 15. ARI by Factor Correlation (Part 4)

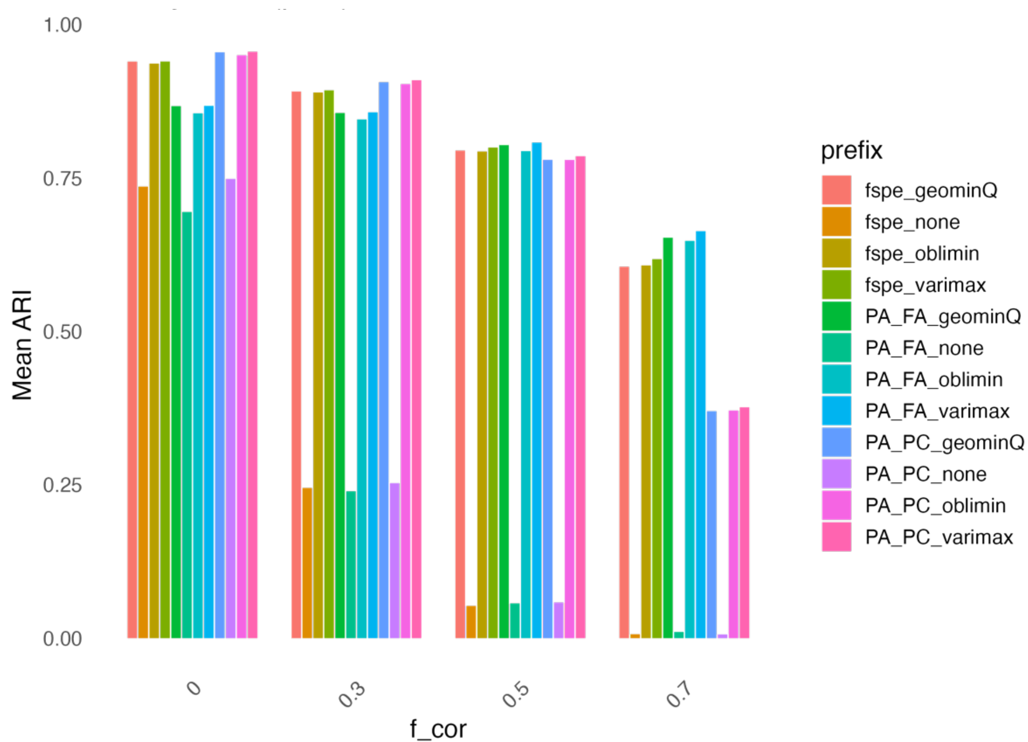

Figure 16. ARI by Factor Correlation (Part 5)

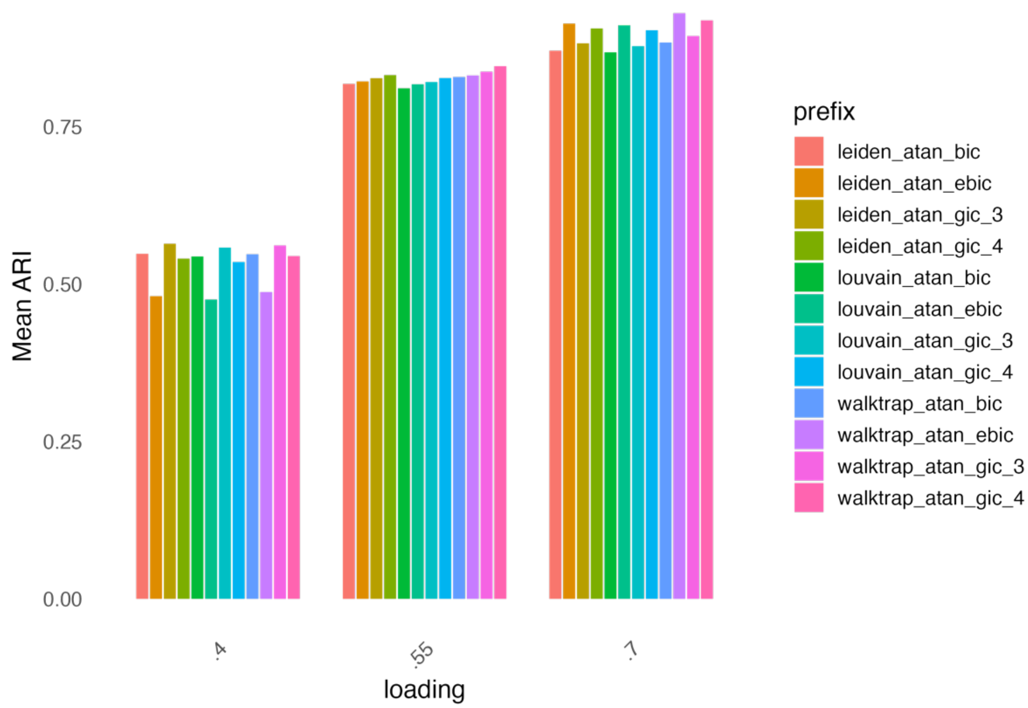

Figure 17. ARI by Factor Loading (Part 1)

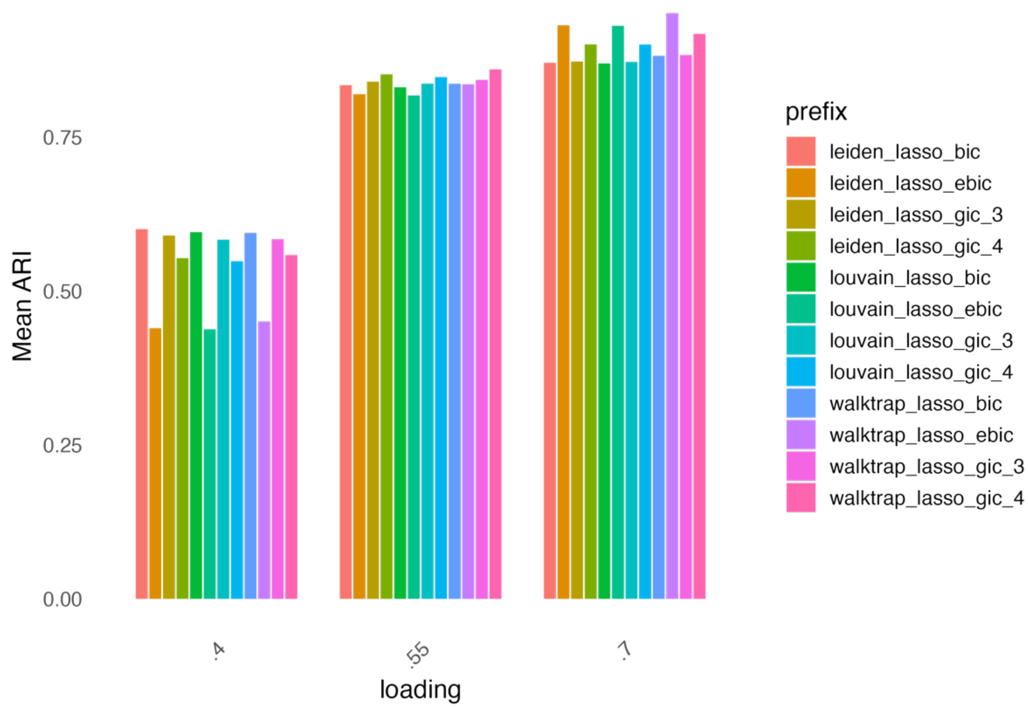

Figure 18. ARI by Factor Loading (Part 2)

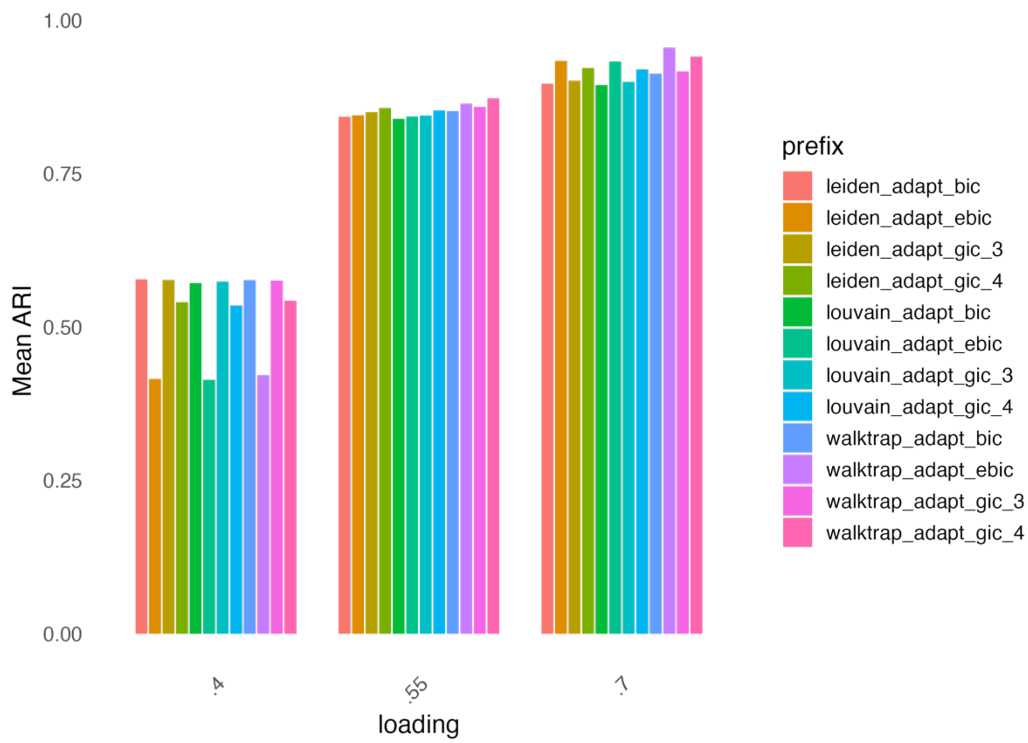

Figure 19. ARI by Factor Loading (Part 3)

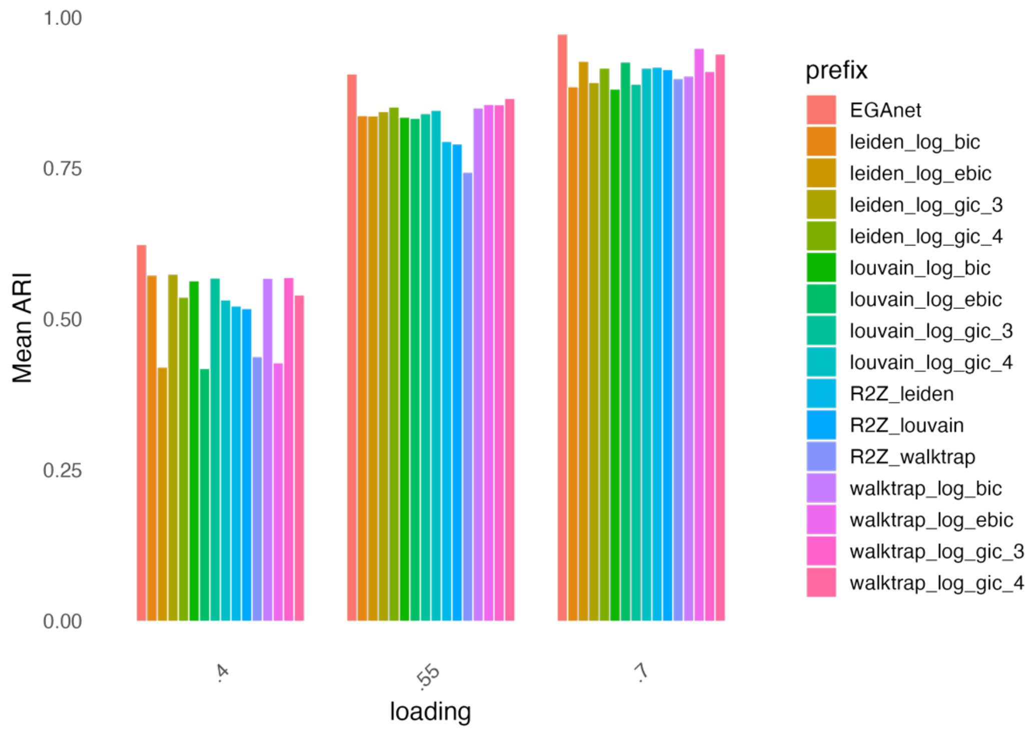

Figure 20. ARI by Factor Loading (Part 4)

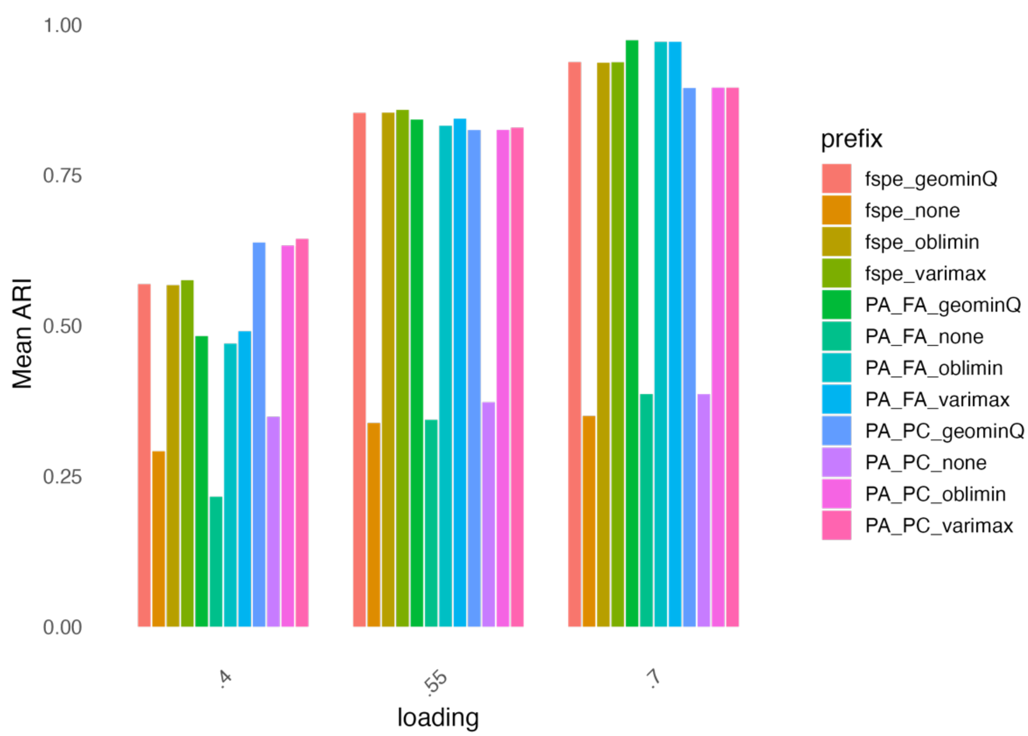

Figure 21. ARI by Factor Loading (Part 5)

These findings should be intuitive; when clusters occupy distinct areas in variable-space (high factor loadings, low factor correlations), they are more identifiable.

Discussion

These findings provide reason to be optimistic. First, the typical approach of parallel analysis to select a factor model, then rotating that solution was quite effective. There was no appreciable difference between PCA/EFA or rotation selection, although *unrotated* components performed poorly. Thus, the most actionable insights are that all state-of-the-art dimension detection approaches perform well for assessing the total dimensionality, given a large enough sample, but factor models should be rotated before assessing variable loadings.

While EGAnet was remarkably effective in the unidimensional condition, a researcher intent on using parallel analysis could use EGAnet only as a unidimensionality check, or employ a different test of unidimensionality, such as *unidim* (Revelle & Condon, 2025). Therefore, there is little need for researchers to deviate from these well-trodden paths.

Further, there is a clear path towards ensuring a high level of performance in dimension assessment through obtaining a large sample size. There was a monotonic relationship between sample size and ARI/accuracy, in some methods exceeding .95 for the highest sample size and factor correlations of 0.0 and 0.3. Even at the 0.5 level of factor correlation, numerous methods were able to achieve >.90 performance on ARI and accuracy. Thus, it seems even relatively disagreeable data can be factored given enough observations.

One might be discouraged by the impact of some inherent characteristics of data on the recoverability of their dimensionality. Indeed, low factor loadings or high factor intercorrelations may be difficult to avoid. However, while factor correlation was the most impactful predictor, most of its effect was in the transition from .5 to .7, at which point accuracy and ARI degraded sharply. This is a very high factor correlation that is probably not representative of usual data in psychology.

The cost of a study often scales linearly with the number of participants and usually researchers are in the unfortunate position of needing to conserve resources and must balance statistical power against financial constraint. A prudent question then is how many observations are needed to do an exploratory factor analysis. As should be obvious, this answer is difficult to answer based on the confluence of impactful variables for which the researcher should use their best judgment. However, there is a stark jump in performance from a sample of 200 to one of 400. Absent any other information, 400 seems like a reasonable suggestion. However, if one has reason to expect items load strongly onto their respective factors, which among themselves are orthogonal, this requirement could be relaxed. Further study into the impact of related observations (e.g., longitudinal observations with subjects on the same scale) on sample size requirements would be of value.

Making recommendations beyond a minimum sample size is difficult. Based on these findings, minimizing factor correlations and maximizing item loadings onto factors is the natural conclusion, but presupposes a level of researcher control that may not be possible. Best practices for EFA are to anticipate both the factor domains to query and the quality of items intended to tap those domains (Watkins, 2018). In psycholexical studies, EFA and other dimensionality methods are used as an atheoretical means of resolving the number of factor domains, which mostly precludes judging the quality of items beyond having a face valid personological link. In other psychological areas (for which these findings are more apt), where a researcher aims to test a particular conceptualization of a theory, this is less problematic. However, recovering a lower-dimensional structure does not guarantee that the researcher has recovered all salient dimensions, or even the important ones. Nonetheless, it is usually possible to exclude items that will not be strong indicators of the factor domain, though correlated factors may at times be unavoidable even with judicious item selection.

This study sought to answer which dimension detection algorithm is best. In that process, it recovered the truism, *garbage in, garbage out*. It bears emphasizing the primacy of data quality over algorithm. However, there was enough heterogeneity among algorithms to make some suggestions. In all cases, *EGAnet* is among the best choices. This, along with its suite of tools—notably unique variable analysis—makes it compelling as the exploratory factor analysis method of choice.

At low sample sizes, multidimensional structures without high factor intercorrelations were identified best by parallel analysis of principal components, performing slightly better than *EGAnet*. If one disregards (by choice or necessity) the previous exhortation to collect a large sample size, then parallel analysis would be a sensible choice.

Though *EGAnet* performs admirably, there may be room for improvement. At higher sample sizes in multidimensional cases, other regularization and information criteria outperform the EBICGLASSO paradigm, both in terms of accuracy/ARI and absolute and bias error. The BIC criterion performed similarly to the GIC_3 and GIC_4 criteria, which means the EBIC framework could still be used, as the BIC is identical to the EBIC with hyperparameter γ set to zero. Based on these data, the adaptive lasso is a compelling alternative to the graphical lasso.

Conclusions

The aims of this study were to test modern dimension reduction approaches and the conditions under which such approaches are most appropriate. The core finding of this work is that choice of approach is less important than careful study design prior to data collection.

Critically, a large sample is essential. As a starting point, 400 observations is recommended, although these data find incremental improvements up to 1,000, and likely would find improvements beyond that, as others have (H. F. Golino & Epskamp, 2017). Poor item-factor loadings and strong factor intercorrelations also hamper performance, although these can be ameliorated by more data, except in extreme cases. The other manipulated conditions were minimally impactful.

The *EGAnet* package performs among the best under all conditions and is never substantially weaker than others. That, in addition to the host of other tools in its framework, makes is an obvious choice for researchers performing exploratory factor analysis. Its design makes it especially strong in detecting unidimensional datasets, although it may be slightly improved through consideration of other regularizing schemes.

Chapter 3: Study 2

Introduction

One of the most compelling results favoring the Big Five model of personality was done by Goldberg (1990), who found similar results across factor analytic methods. In that paper, results were interpreted as having generated consistent factor structures across a combination of five factor extraction methods (principal components, principal factors, alpha factoring, image factoring, and maximum-likelihood) and two rotation algorithms (varimax and oblimin). Although the conclusion that personality is well-represented by five factors has faced considerable scrutiny (Block, 1995; De Raad et al., 2010; Paunonen & Jackson, 2000), the statistical validity of these methods has had less consideration.

This study consists of two undertakings (Studies A and B) which continue in that spirit by first (in study A) simulating data akin to that of Saucier & Goldberg (1996) (e.g., matching scaling, sample size, factor loadings, etc.), but with known factor structures, then benchmarking the performance of various dimension detection algorithms to apply (in Study B) the best approach to the original dataset of Saucier & Goldberg. This will allow for an empirically validated method for identifying wide bandwidth traits, rather than operating on the assumption that the factor analytic approach is the correct one.

These findings will inform whether the optimal structure was indeed recovered in those past works, though of course they do not address the demographic homogeneity from which they were derived nor the limited size of trait-descriptive adjectives tested, which limits the generalizability of these (and those) findings.

Methods (Study 2A)

Data-Generating Mechanism

To assess performance of these various algorithms, datasets were simulated using a Monte Carlo design in which three parameters in the data generative process were systematically varied with a similar approach to past works in this vein (Garrido et al., 2016; H. Golino et al., 2020). These parameters (Table 7) include number of factors, items per factor imbalance, and scaling method (observation- or variable-wise). The *latentFactoR* package (Christensen, Nieto Canaveras, et al., 2023) will again be used to generate these data.

Datasets (regenerated one hundred times per condition) were reproduced from a combination of parameters to best replicate the conditions found in the Saucier & Goldberg data, which contains 899 responses to 435 variables. The findings of that study suggested an a priori assumption of five factors, with item-factor loadings at approximately .4, generally weak cross-loadings (.1, on average), and a very high number of items per factor, at an average of 87 per factor. Sample size replicated that of the original dataset (*n*=899). However, since that dataset was pooled from four samples using two rating scales, the simulated dataset was similarly generated. The majority of responses (*n*=636) were on a seven-step rating, with the remainder (*n*=263) on an eight-step rating scale. In the original Saucier & Goldberg dataset, all items were ipsatized prior to aggregation. In this work, datasets within a condition were either all ipsatized (Z-scored) across observation or standardized (Z-scored) across item in order to compare the effects of standardizing and ipsatizing. Although Saucier & Goldberg (1996) ipsatized their data, ipsative data do not produce a full-rank matrix, which limits the dimension reduction approaches available and may have other downstream impacts on dimension recovery. Scaled data were tested simultaneously to determine whether this difference had any distinct effect on the outcome of dimension detection approaches amenable to both.

To reasonably attempt avoiding biasing the solution to five factors, the simulated datasets considered factor solutions of 3-6 factors, while still using 435 variables. As well, data were simulated to either have equal numbers of items per factor (to the extent possible dividing 435 items among varying factors) or uneven numbers (drawn from an exponential distribution). In the event either parameter influenced the optimal approach, all approaches representing an optimum for a given level of a parameter were considered. The same measures of performance in the past studies were used.

Number of factors

Structures ranging from two to eight factors were simulated. Factor solutions of two (Digman, 1997; D. Liu & Campbell, 2017), and three (De Raad et al., 2010), are rather well-known, though none as prevalent as the five- and six-factor solutions respectively represented by the Big Five (Goldberg, 1990) and HEXACO (Lee & Ashton, 2004) models.

Items per factor Imbalance

Items were either allocated equally (to the extent possible) across factors or drawn from an exponential distribution, in which the largest grouping of items can be expected to be considerably larger than the smallest. This latter case was meant to be more representative of typical structures of personality, in which the emergent structure is often imbalanced, although the final scales from which those structures are based may have subsets of equal numbers of terms across factors.

Scaling

In the “ipsative” condition, observations were standardized (centered and z-scored); in the “scaled” condition, variables were standardized. Note that in this latter condition, variables were standardized within their seven- or eight-step categorical sets, then pooled after scaling.

Non-varied parameters

The majority of responses (*n*=636) were on a seven-step rating, with the remainder (*n*=263) on an eight-step rating scale. Naturally, this makes the total sample size 899.

More additional steps were taken in simulating these data to generate realistic response datasets. Cross-loadings were randomly drawn from a normal distribution *N*(0, .05) for all items. Skewness was also introduced for each item as a random uniform distribution of -2 to 2 in increments of .50.

Table 7. Monte Carlo data generation parameters

Condition	**Levels**
Number of factors	2,3,4,5,6,7,8
Items per factor imbalance	Equally or exponentially distributed
Scaling	Ipsative (observation-wise) or scaled (variable-wise)

The set and levels of conditions allowed for a full factorial design: 7x2x2, or 28 total combinations. Each combination was simulated 100 times, for a total of 2800 data matrices. Pearson correlation matrices were computed from each of the matrices.

Regularization Network Estimation

The network estimation approaches were the non-convex methods of GLASSO, MB, and TIGER, as well as the unregularized zero-order correlation matrix. To select a single network from all but the zero-order networks, different information criteria were used. These were RIC and eBIC.

Clustering Algorithms

Algorithms used in this study include a subset of the same as those used in study 1, namely the Louvain, Leiden and Walktrap algorithms. Based on preliminary findings, as well as this author's prior experience with datasets of a larger *p*, more traditional computer science-grounded clustering algorithms were also included. They included all methods and indices from the *NbClust* package (3.0.1; Charrad et al., 2014) that converged in a reasonable amount of time with mean ARI above .50 on a 1% of the simulated datasets. Ultimately, they were Ward's minimum-variance clustering and average linkage clustering. Internal validity indices for those algorithms were Krzanowski-Lai and Davies-Bouldin indices. Other high-performing algorithms were considered as well, including spectral clustering, affinity propagation, HDBSCAN, and gaussian mixture modeling.

Computational Aspects

All data generation and analyses were performed using R Version 4.4.1 (R Core Team, 2022). Data generation was performed using the *latentFactoR* package (version 0.0.6; Christensen, Nieto Canaveras, et al., 2023). Regularization was done using the *huge* package (version 1.3.5; Jiang et al., 2021). Walktrap, Leiden, and Louvain community detection algorithms were run with the *igraph* package (version 2.1.1; Csárdi et al., 2024). FA/PCA and rotations were implemented from the *psych* package (version 2.4.6; Revelle, 2024). Ward's minimum-variance clustering, average linkage clustering, Krzanowski-Lai index, and Davies-Bouldin index were implemented from the *NbClust* package (3.0.1; Charrad et al., 2014). Spectral clustering, affinity propagation, HDBSCAN, and gaussian mixture modeling (plus Adjusted Rand Index), were, respectively, implemented from packages *Spectrum* (version 1.1; C.

R. John & Watson, 2020), *apcluster* (version 1.4.13; Bodenhofer et al., 2011), *dbscan* (version 1.2.0; Hahsler et al., 2019), and *mclust* (version 6.1.1; Scrucca et al., 2023).

Results

There are two main findings from this study. The finding with the greatest implication for the subsequent application of these findings to the proposed dataset is that the performance of dimension detection algorithms was severely hampered by ipsatization (Figure 22, Figure 23). The second finding is that for the standardized conditions nearly all dimension reduction algorithms approached perfection, at least as measured by adjusted rand index (Figure 2). As in Study 1, unrotated factors/components performed poorly by ARI, as did affinity propagation (Table 8, Table 9). Mean bias error (Figure 24) and mean absolute error (Figure 25) were also stronger in the ipsatized condition.

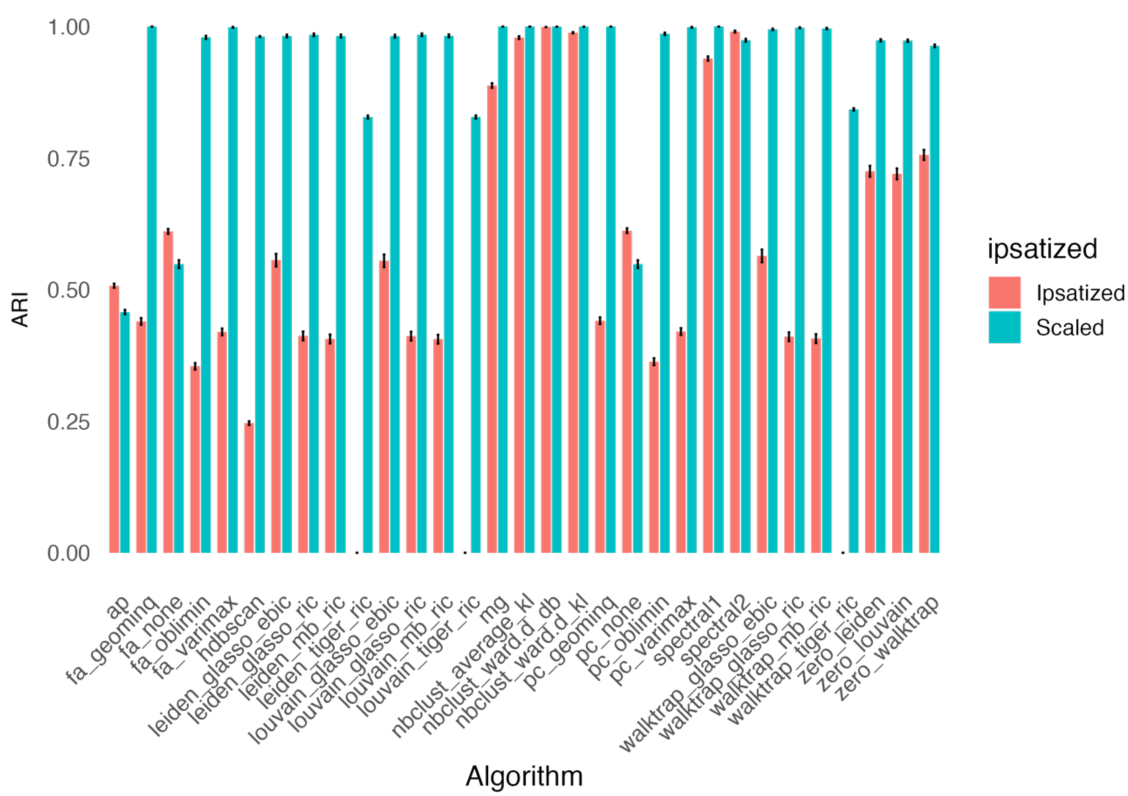

Figure 22. ARI by Algorithms and Scaling Condition

Note 3. 95% Confidence Intervals of the mean are presented in brackets

Note 4. Ap refers to affinity propagation. Spectral 1 and 2 refer to the two methods of spectral clustering in the Spectrum package.

Walktrap, Louvain, Leiden indicate which community detection algorithm was used. MB, TIGER, and GLASSO indicate how the network was regularized. ebic, and RIC refer to which information criterion was used.

Nbclust_ward.d and Nbclust_average refer to Ward's minimum variance clustering and average linkage clustering. The suffixes _kl and _db refer to Krzanowski-Lai and Davies-Bouldin indices.

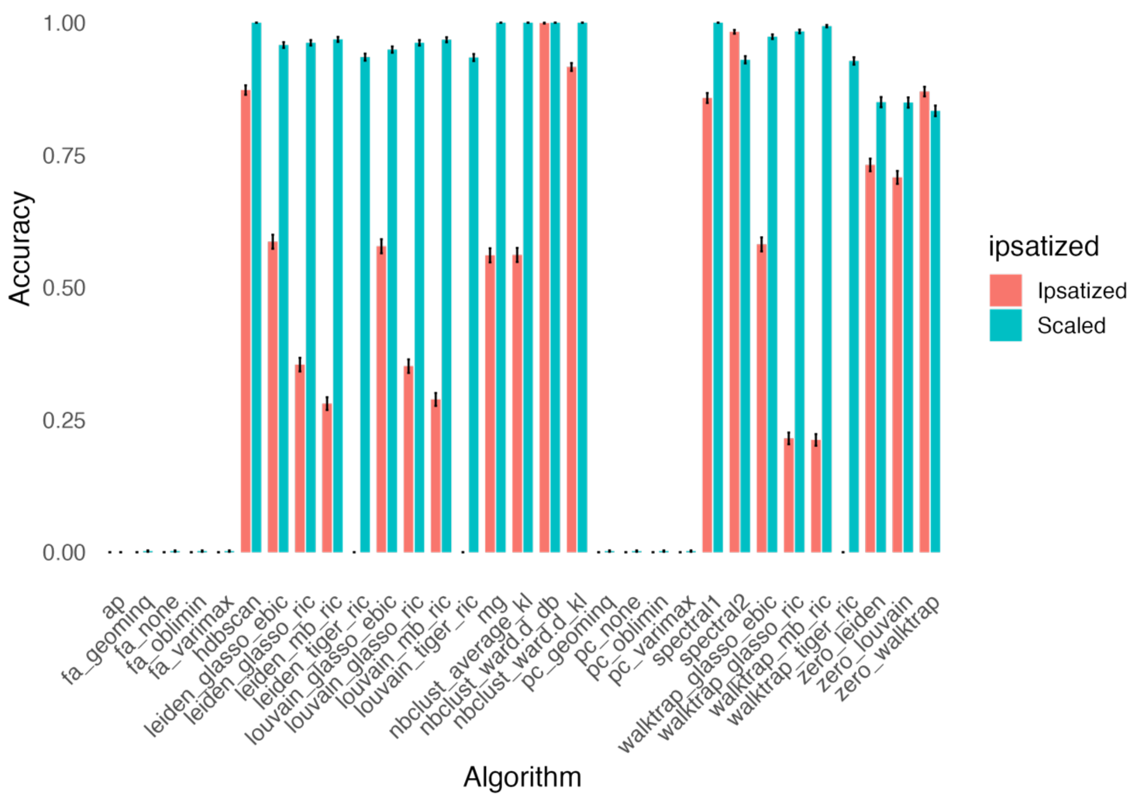

Figure 23. Accuracy by Algorithm and Scaling Condition

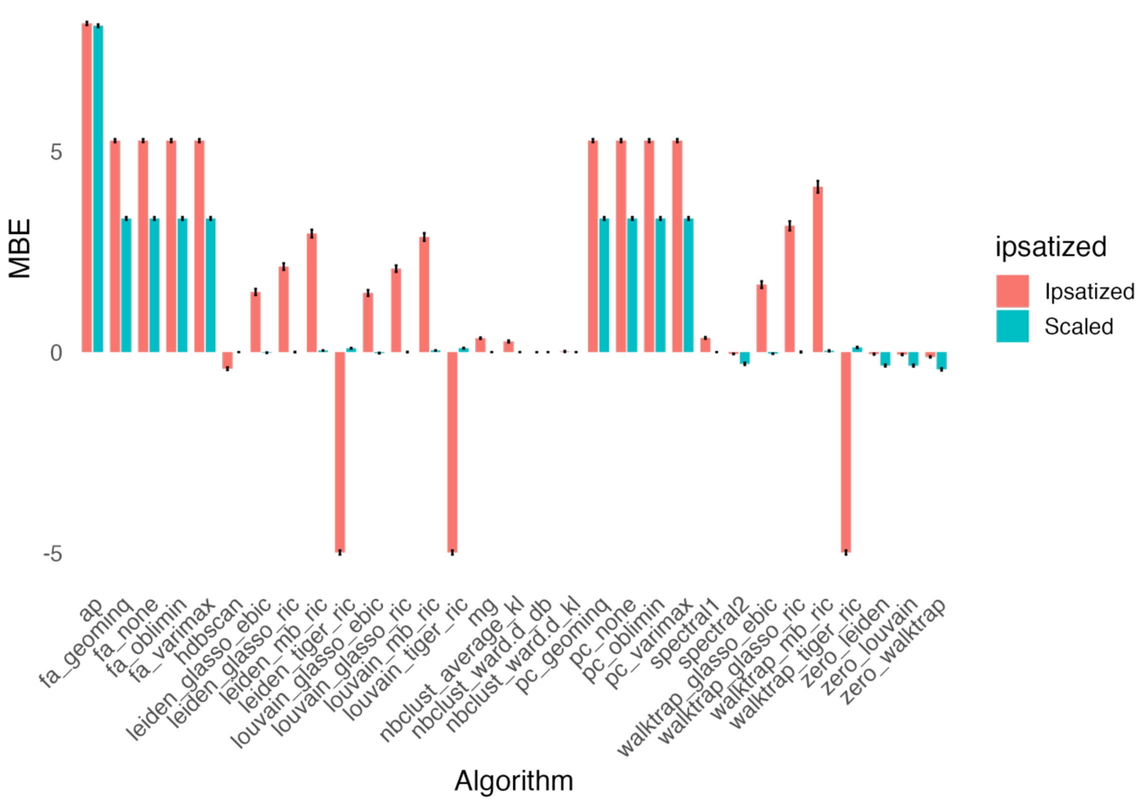

Figure 24. Mean Bias Error by Algorithm and Scaling Condition

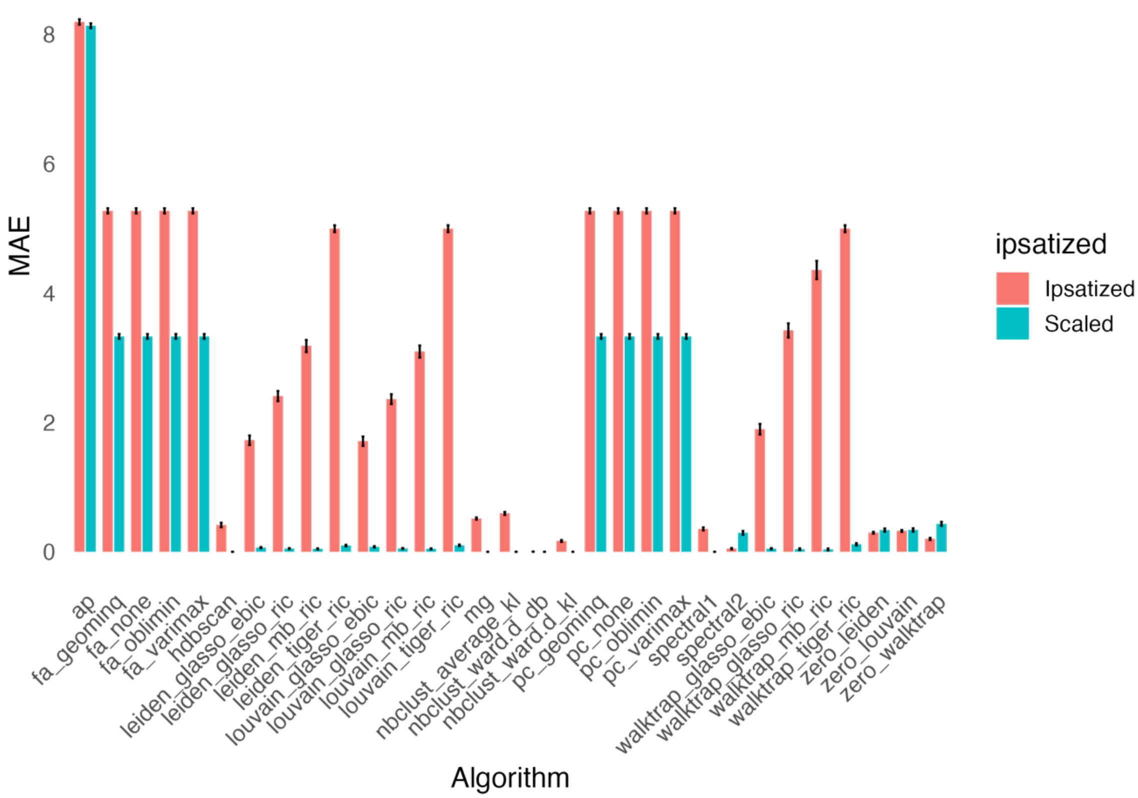

Figure 25. Mean Absolute Error by Algorithm and Scaling Condition

Table 8. Average Performance by Scaling Condition, Standardized Data

Algorithmic Approach	**ARI**	**Accuracy**	**MAE**	**MBE**	**Over/Under Factored?**
ap	.46 [.45, .47]	.00 [.00, .00]	8.13 [8.06, 8.2]	8.13 [8.06, 8.2]	Over
fa_geominq	1.00 [1.00, 1.00]	.00 [.00, .00]	3.33 [3.26, 3.4]	3.33 [3.26, 3.4]	Over
fa_none	.55 [.53, .56]	.00 [.00, .00]	3.33 [3.26, 3.4]	3.33 [3.26, 3.4]	Over
fa_oblimin	.98 [.97, .99]	.00 [.00, .00]	3.33 [3.26, 3.4]	3.33 [3.26, 3.4]	Over
fa_varimax	1.00 [1.00, 1.00]	.00 [.00, .00]	3.33 [3.26, 3.4]	3.33 [3.26, 3.4]	Over
hdbscan	.98 [.98, .98]	1.00 [1.00, 1.00]	0.00 [0.00, 0.00]	0.00 [0.00, 0.00]	Neither
leiden_GLASSO_ebic	.98 [.98, .99]	.96 [.95, .97]	0.06 [0.05, 0.08]	-0.02 [-0.03, 0]	Under
leiden_GLASSO_ric	.98 [.98, .99]	.96 [.95, .97]	0.05 [0.04, 0.06]	0.00 [-0.01, 0.02]	Neither
leiden_mb_ric	.98 [.98, .99]	.97 [.96, .98]	0.05 [0.03, 0.06]	0.04 [0.02, 0.05]	Over
leiden_tiger_ric	.83 [.82, .83]	.94 [.92, .95]	0.10 [0.07, 0.12]	0.10 [0.07, 0.12]	Over
louvain_GLASSO_ebic	.98 [.98, .99]	.95 [.94, .96]	0.08 [0.06, 0.1]	-0.03 [-0.04, -0.01]	Under
louvain_GLASSO_ric	.98 [.98, .99]	.96 [.95, .97]	0.05 [0.04, 0.07]	0.00 [-0.01, 0.02]	Neither
louvain_mb_ric	.98 [.98, .99]	.97 [.96, .98]	0.05 [0.03, 0.06]	0.04 [0.03, 0.05]	Over
louvain_tiger_ric	.83 [.82, .83]	.93 [.92, .95]	0.10 [0.08, 0.12]	0.10 [0.07, 0.12]	Over
mg	1.00 [1.00, 1.00]	1.00 [1.00, 1.00]	0.00 [0.00, 0.00]	0.00 [0.00, 0.00]	Neither
nbclust_average_kl	1.00 [1.00, 1.00]	1.00 [1.00, 1.00]	0.00 [0.00, 0.00]	0.00 [0.00, 0.00]	Neither
nbclust_ward.d_db	1.00 [1.00, 1.00]	1.00 [1.00, 1.00]	0.00 [0.00, 0.00]	0.00 [0.00, 0.00]	Neither
nbclust_ward.d_kl	1.00 [1.00, 1.00]	1.00 [1.00, 1.00]	0.00 [0.00, 0.00]	0.00 [0.00, 0.00]	Neither
pc_geominq	1.00 [1.00, 1.00]	.00 [.00, .00]	3.33 [3.26, 3.4]	3.33 [3.26, 3.4]	Over
pc_none	.55 [.53, .56]	.00 [.00, .00]	3.33 [3.26, 3.4]	3.33 [3.26, 3.4]	Over
pc_oblimin	.99 [.98, .99]	.00 [.00, .00]	3.33 [3.26, 3.4]	3.33 [3.26, 3.4]	Over
pc_varimax	1.00 [1.00, 1.00]	.00 [.00, .00]	3.33 [3.26, 3.4]	3.33 [3.26, 3.4]	Over
spectral1	1.00 [1.00, 1.00]	1.00 [1.00, 1.00]	0.00 [0.00, 0.00]	0.00 [0.00, 0.00]	Neither
spectral2	.97 [.97, .98]	.93 [.92, .94]	0.29 [0.24, 0.35]	-0.29 [-0.35, -0.24]	Under
walktrap_GLASSO_ebic	.99 [.99, 1.00]	.97 [.97, .98]	0.05 [0.03, 0.06]	-0.04 [-0.06, -0.02]	Under
walktrap_GLASSO_ric	1.00 [1.00, 1.00]	.98 [.98, .99]	0.04 [0.01, 0.07]	0.00 [-0.03, 0.03]	Neither
walktrap_mb_ric	1.00 [.99, 1.00]	.99 [.99, 1.00]	0.04 [0.00, 0.07]	0.03 [0.00, 0.06]	Over
walktrap_tiger_ric	.84 [.84, .85]	.93 [.91, .94]	0.12 [0.08, 0.15]	0.12 [0.08, 0.15]	Over
zero_leiden	.97 [.97, .98]	.85 [.83, .87]	0.34 [0.28, 0.39]	-0.34 [-0.39, -0.28]	Under
zero_louvain	.97 [.97, .98]	.85 [.83, .87]	0.34 [0.29, 0.39]	-0.34 [-0.39, -0.29]	Under
zero_walktrap	.96 [.96, .97]	.83 [.81, .85]	0.43 [0.37, 0.49]	-0.43 [-0.49, -0.37]	Under

Table 9. Average Performance by Scaling Condition, Ipsatized Data

Algorithmic Approach	**ARI**	**Accuracy**	**MAE**	**MBE**	**Over/Under Factored?**
ap	.51 [.5, .52]	.00 [.00, .00]	8.19 [8.1, 8.27]	8.19 [8.10, 8.27]	Over
fa_geominq	.44 [.43, .45]	.00 [.00, .00]	5.27 [5.19, 5.35]	5.27 [5.19, 5.35]	Over
fa_none	.61 [.6, .62]	.00 [.00, .00]	5.27 [5.19, 5.35]	5.27 [5.19, 5.35]	Over
fa_oblimin	.35 [.34, .37]	.00 [.00, .00]	5.27 [5.19, 5.35]	5.27 [5.19, 5.35]	Over
fa_varimax	.42 [.41, .43]	.00 [.00, .00]	5.27 [5.19, 5.35]	5.27 [5.19, 5.35]	Over
hdbscan	.25 [.24, .25]	.87 [.86, .89]	0.41 [0.35, 0.48]	-0.41 [-0.48, -0.35]	Under
leiden_GLASSO_ebic	.56 [.53, .58]	.59 [.56, .61]	1.72 [1.58, 1.87]	1.5 [1.35, 1.65]	Over

leiden_GLASSO_ric	.41 [.4, .43]	.35 [.33, .38]	2.41 [2.25, 2.56]	2.13 [1.97, 2.29]	Over
leiden_mb_ric	.41 [.39, .42]	.28 [.26, .3]	3.18 [3, 3.36]	2.95 [2.76, 3.14]	Over
leiden_tiger_ric	.00 [.00, .00]	.00 [.00, .00]	4.99 [4.89, 5.1]	-4.99 [-5.1, -4.89]	Under
louvain_GLASSO_ebic	.55 [.53, .58]	.58 [.55, .6]	1.71 [1.57, 1.85]	1.47 [1.32, 1.62]	Over
louvain_GLASSO_ric	.41 [.4, .43]	.35 [.33, .38]	2.36 [2.21, 2.51]	2.08 [1.92, 2.24]	Over
louvain_mb_ric	.41 [.39, .42]	.29 [.26, .31]	3.09 [2.91, 3.28]	2.87 [2.68, 3.06]	Over
louvain_tiger_ric	.00 [.00, .00]	.00 [.00, .00]	4.99 [4.89, 5.1]	-4.99 [-5.1, -4.89]	Under
mg	.89 [.88, .9]	.56 [.53, .59]	0.51 [0.48, 0.55]	0.35 [0.31, 0.39]	Over
nbclust_average_kl	.98 [.97, .98]	.56 [.54, .59]	0.59 [0.55, 0.64]	0.26 [0.21, 0.32]	Over
nbclust_ward.d_db	1.00 [1.00, 1.00]	1.00 [1.00, 1.00]	0.00 [0.00, 0.00]	0.00 [0.00, 0.00]	Neither
nbclust_ward.d_kl	.99 [.99, .99]	.92 [.9, .93]	0.17 [0.14, 0.2]	0.01 [-0.02, 0.04]	Over
pc_geominq	.44 [.43, .45]	.00 [.00, .00]	5.27 [5.19, 5.35]	5.27 [5.19, 5.35]	Over
pc_none	.61 [.6, .62]	.00 [.00, .00]	5.27 [5.19, 5.35]	5.27 [5.19, 5.35]	Over
pc_oblimin	.36 [.35, .38]	.00 [.00, .00]	5.27 [5.19, 5.35]	5.27 [5.19, 5.35]	Over
pc_varimax	.42 [.41, .43]	.00 [.00, .00]	5.27 [5.19, 5.35]	5.27 [5.19, 5.35]	Over
spectral1	.94 [.93, .95]	.86 [.84, .88]	0.35 [0.31, 0.4]	0.35 [0.31, 0.4]	Over
spectral2	.99 [.99, .99]	.98 [.98, .99]	0.05 [0.03, 0.07]	-0.04 [-0.06, -0.02]	Under
walktrap_GLASSO_ebic	.56 [.54, .59]	.58 [.56, .61]	1.89 [1.73, 2.05]	1.68 [1.51, 1.85]	Over
walktrap_GLASSO_ric	.41 [.39, .43]	.22 [.19, .24]	3.42 [3.21, 3.63]	3.15 [2.92, 3.37]	Over
walktrap_mb_ric	.41 [.39, .42]	.21 [.19, .23]	4.35 [4.08, 4.63]	4.12 [3.83, 4.4]	Over
walktrap_tiger_ric	.00 [.00, .00]	.00 [.00, .00]	4.99 [4.89, 5.1]	-4.99 [-5.1, -4.89]	Under
zero_leiden	.73 [.7, .75]	.73 [.71, .75]	0.29 [0.27, 0.32]	-0.05 [-0.08, -0.02]	Under
zero_louvain	.72 [.7, .74]	.71 [.68, .73]	0.32 [0.29, 0.35]	-0.06 [-0.1, -0.03]	Under
zero_walktrap	.76 [.74, .78]	.87 [.85, .89]	0.2 [0.17, 0.23]	-0.12 [-0.15, -0.09]	Under

Some factor analytic-based algorithms identified superfluous factors, though items did not load strongly onto them. However, unrotated factors and principal components, as well as affinity propagation performed unsatisfactorily.

ANOVAs of ARI (Figure 26), MBE (Figure 27), MAE (Figure 28), and accuracy (Figure 29) generally revealed significant effects of factor number, ipsatization, and an interaction between factor number and ipsatization.

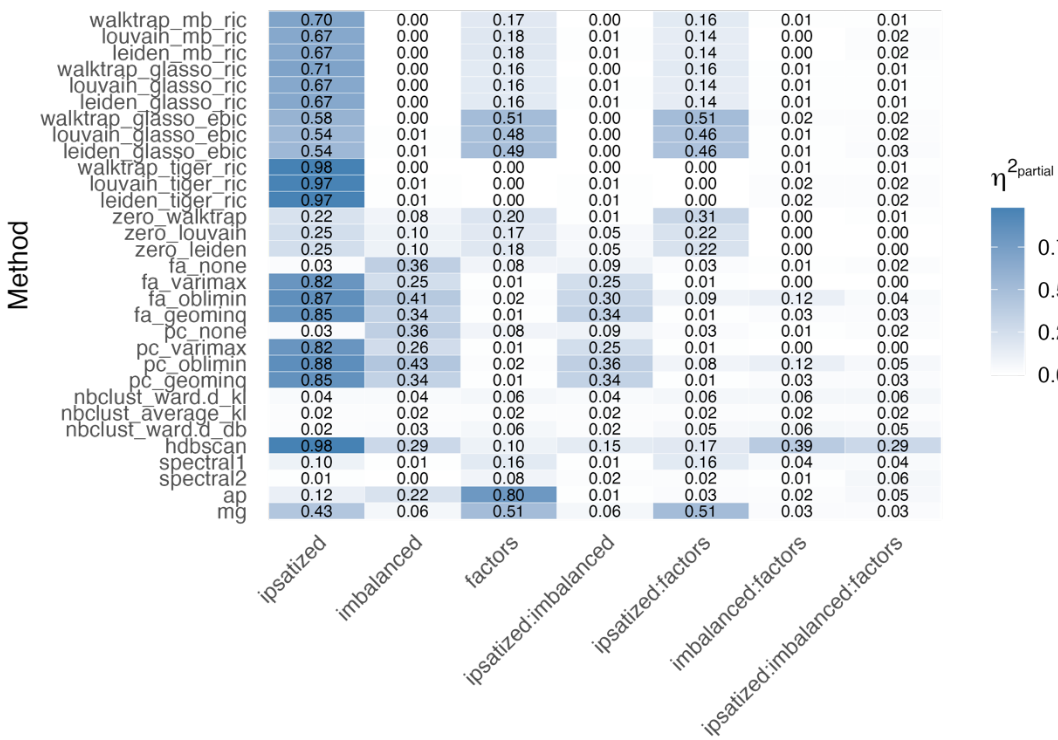

Figure 26. Heatmap of Partial Eta Squared for ARI by Term Interactions

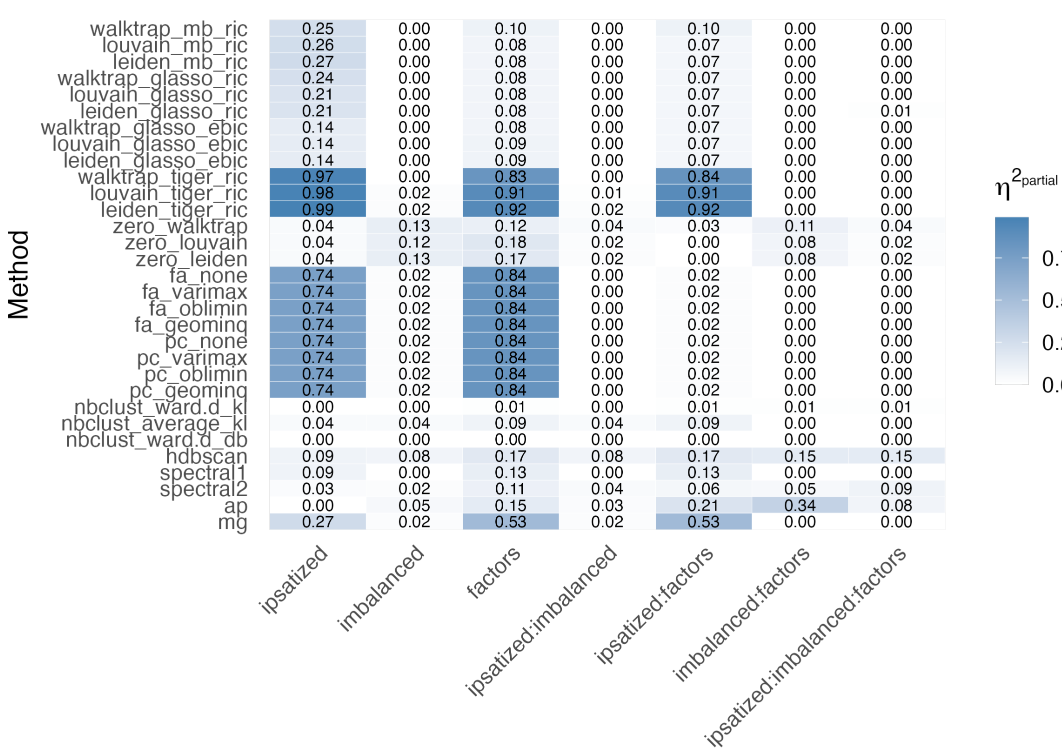

Figure 27. Heatmap of Partial Eta Squared for MBE by Term Interactions

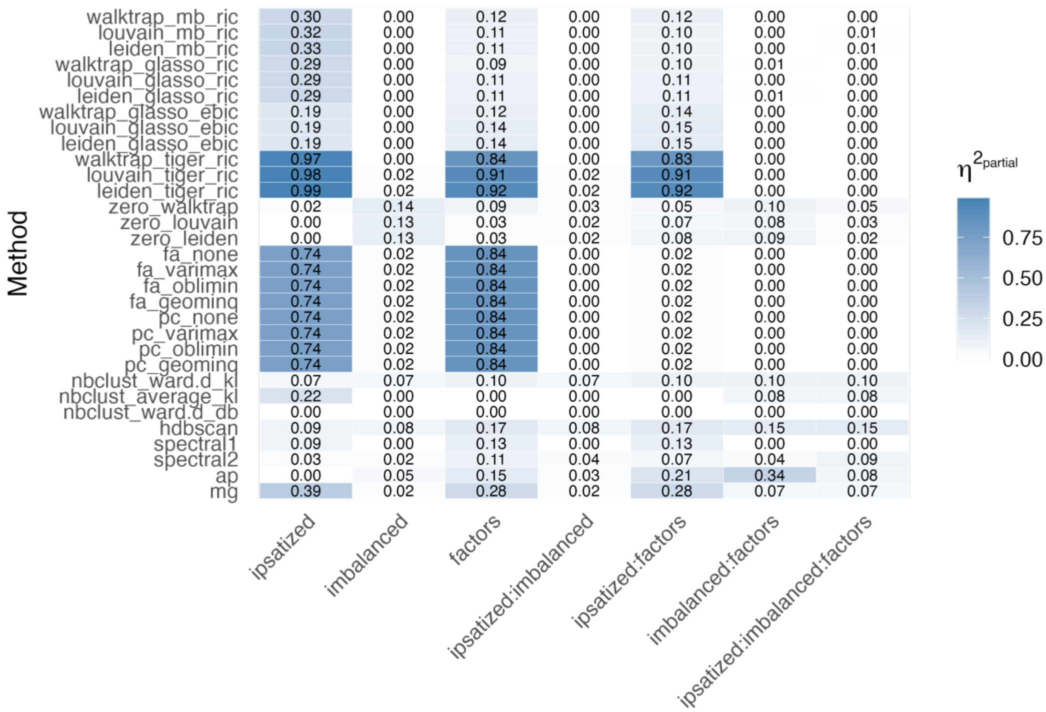

Figure 28. Heatmap of Partial Eta Squared for MAE by Term Interactions

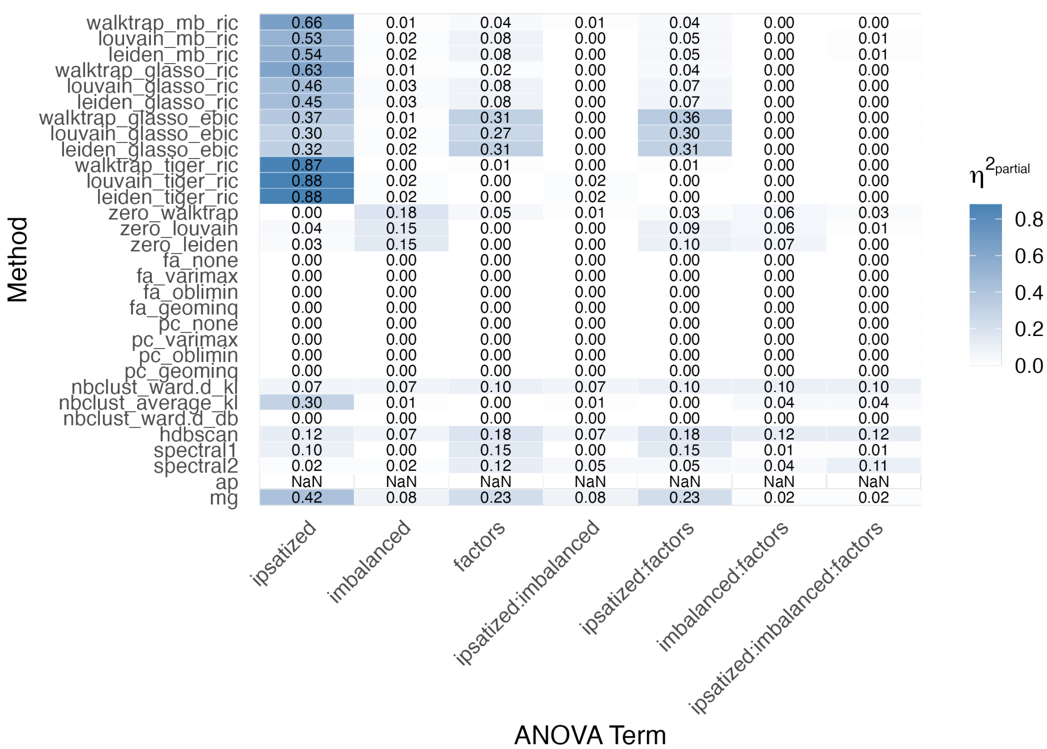

Figure 29. Heatmap of Partial Eta Squared for Accuracy by Term Interactions

This interaction arises because ipsatization limits algorithms from identifying structures with small numbers of factors, as can be seen by the trend for Accuracy and ARI to increase as the number of factors increased (Figure 30). In the ipsatized condition, MAE and MBE broadly decreased as factor number grew (Figure 32, Figure 33). The factor analytic approaches are a notable exception to this trend (Figure 31).

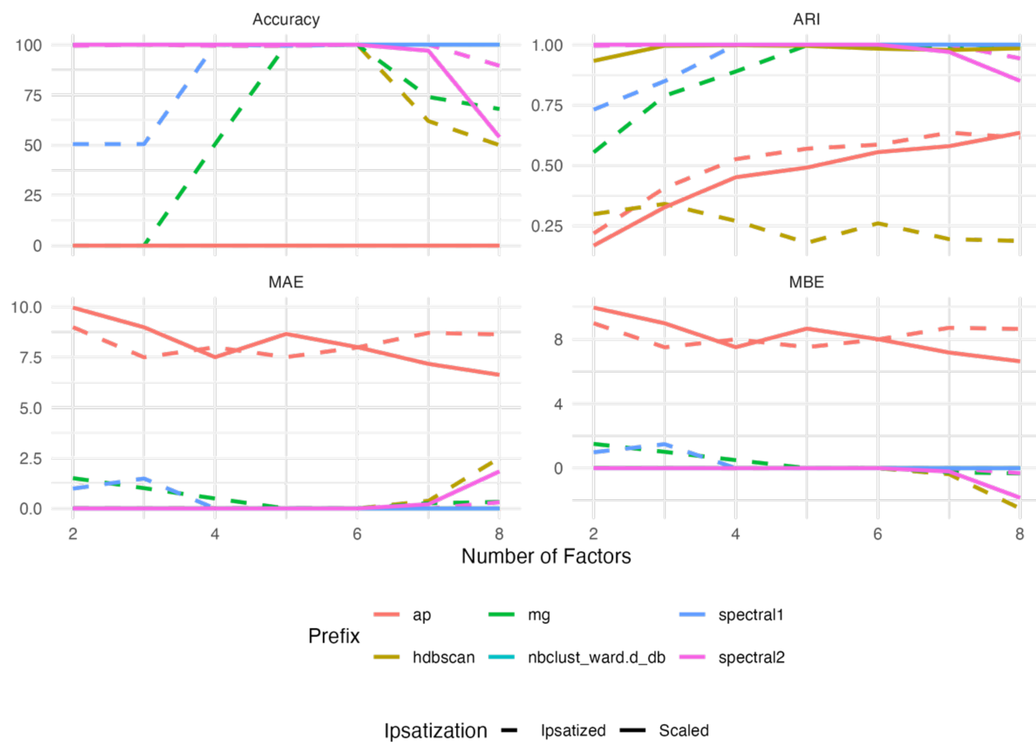

Figure 30. Performance by Factor Level and Scaling Condition (Part 1)

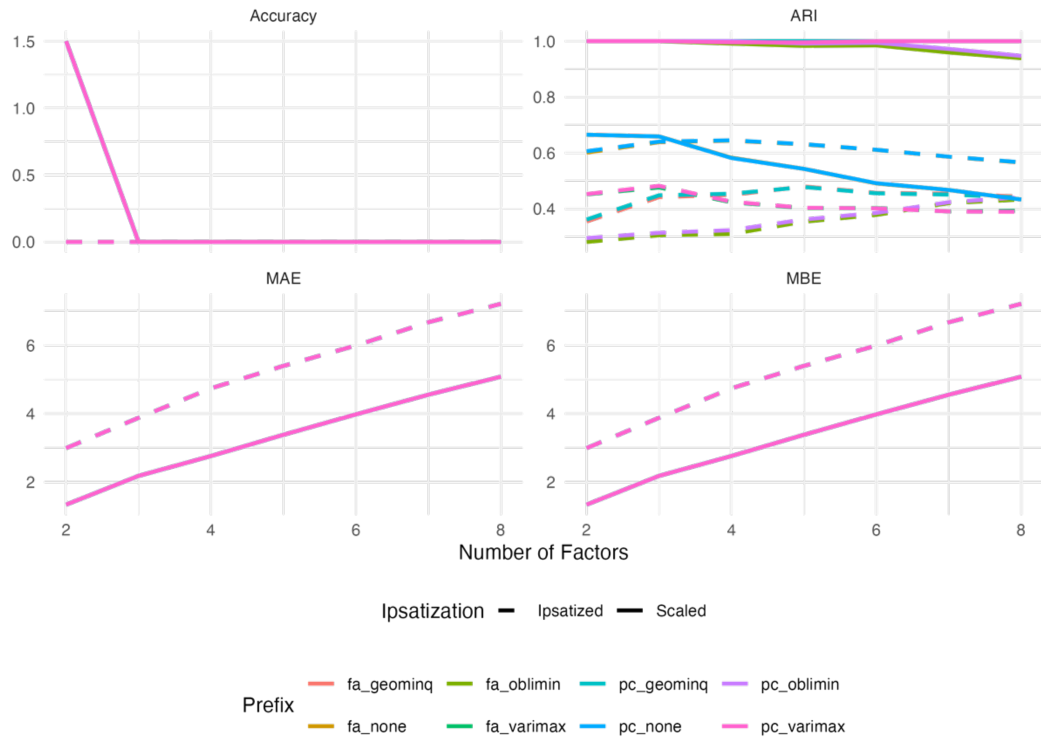

Figure 31. Performance by Factor Level and Scaling Condition (Part 2)

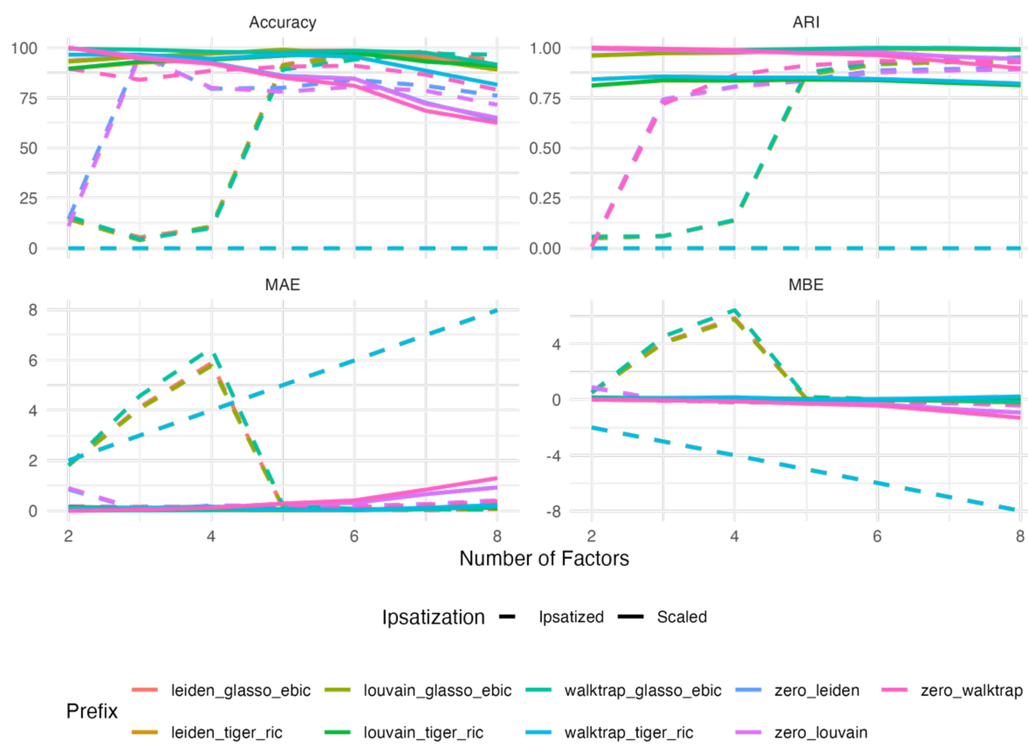

Figure 32. Performance by Factor Level and Scaling Condition (Part 3)

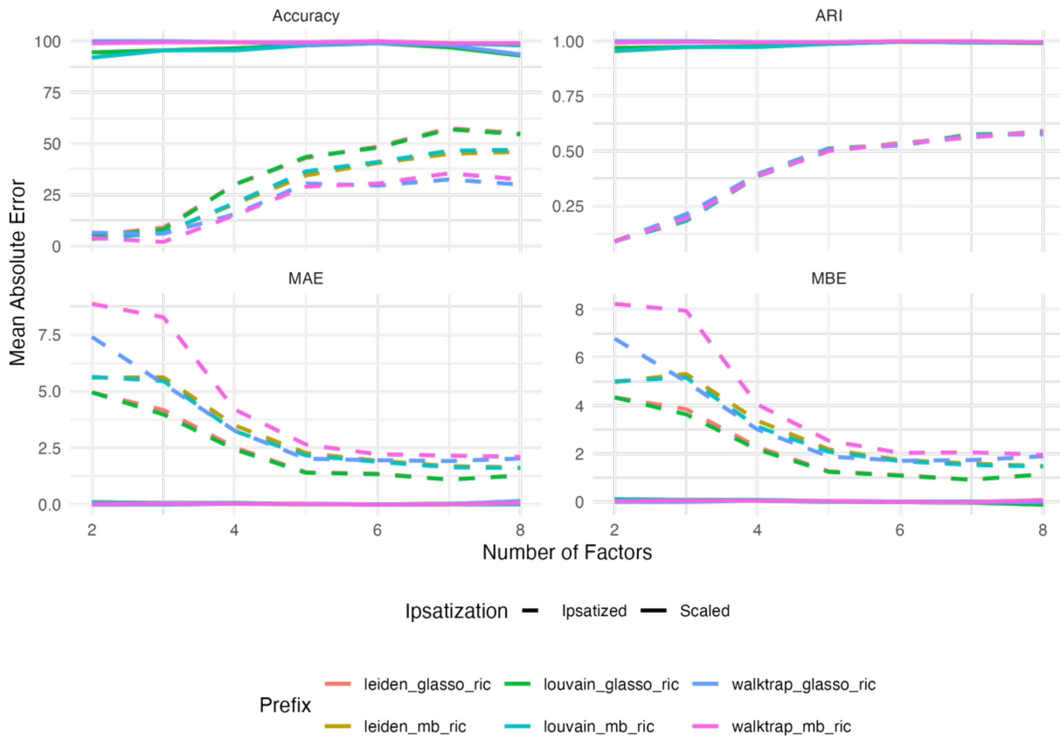

Figure 33. Performance by Factor Level and Scaling Condition (Part 4)

These data are presented in tabular format as well for each outcome across all condition levels (Table 10, Table 11, Table 12, Table 13).

The network psychometric-inspired approaches were relatively unsuccessful for handling ipsatized datasets. This effect seems to be driven by the impact of regularization, as algorithms operating on the zero-order correlation matrix were effective under ipsatization for factor numbers greater than 2. Regularization especially hampered dimension detection under fewer than five factors. The EBICGLASSO approach was effective under ipsatization for factor numbers of 5-8. The TIGER/RIC conditions, however, were never able to identify a connected network in the ipsatized condition.

Imbalance was largely unimpactful, except for factor analytic solutions, which were more effective at clustering in the imbalanced conditions, even across ipsatized conditions. However, factor analytic algorithms consistently overfactored in the ipsatized conditions.

HDBSCAN, peculiarly, was effective at identifying the number of factors but had poor ARI within the ipsatized condition, meaning it consistently recovered the correct number of factors with incorrect groupings within. This may be due to the algorithm misidentifying many nodes as uncluttered "noise" points. In the ipsatized condition, it was more effective in the imbalanced conditions, although it was increasingly less effective in those imbalanced conditions as the factor number grew.

Because there was limited variance in the non-ipsatized condition (most algorithms performed near perfection), it is impossible to infer trends in factor number or imbalancing.

Table 10. Average ARI by Condition

	Scaling		Distribution		Factor Number						
Algorithmic Approach	**Ipsatized**	**Standardized**	**Equal**	**Pareto**	**2**	**3**	**4**	**5**	**6**	**7**	**8**
ap	.51	.46	.52	.45	.19	.37	.49	.53	.57	.61	.62
fa_geominq	.44	1.00	.8	.64	.68	.72	.72	.74	.73	.73	.72
fa_none	.61	.55	.45	.71	.63	.65	.61	.59	.55	.53	.50
fa_oblimin	.35	.98	.77	.57	.64	.65	.65	.67	.68	.69	.69
fa_varimax	.42	1.00	.79	.63	.73	.74	.71	.70	.70	.70	.70
hdbscan	.25	.98	.58	.65	.62	.67	.63	.59	.62	.59	.59
leiden_GLASSO_ebic	.56	.98	.79	.75	.51	.52	.56	.93	.96	.96	.96
leiden_GLASSO_ric	.41	.98	.70	.70	.53	.59	.69	.75	.76	.79	.79
leiden_mb_ric	.41	.98	.69	.69	.52	.58	.68	.74	.77	.78	.79
leiden_tiger_ric	.00	.83	.42	.41	.41	.42	.42	.42	.42	.41	.41
louvain_GLASSO_ebic	.55	.98	.79	.75	.51	.52	.56	.93	.96	.96	.96
louvain_GLASSO_ric	.41	.98	.70	.70	.53	.59	.69	.75	.76	.79	.79
louvain_mb_ric	.41	.98	.69	.69	.52	.58	.68	.74	.77	.78	.79
louvain_tiger_ric	.00	.83	.42	.41	.41	.42	.42	.42	.42	.41	.41
mg	.89	1.00	.96	.93	.78	.89	.94	1.00	1.00	1.00	1.00
nbclust_average_kl	.98	1.00	1.00	.98	1.00	1.00	1.00	1.00	1.00	.94	1.00
nbclust_ward.d_db	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
nbclust_ward.d_kl	.99	1.00	1.00	.99	1.00	1.00	1.00	1.00	1.00	.99	.97
pc_geominq	.44	1.00	.80	.64	.68	.72	.73	.74	.73	.73	.72
pc_none	.61	.55	.45	.71	.64	.65	.61	.59	.55	.53	.50
pc_oblimin	.36	.99	.77	.58	.65	.66	.66	.68	.69	.70	.69
pc_varimax	.42	1.00	.79	.63	.73	.74	.71	.70	.70	.70	.69
spectral1	.94	1.00	.98	.96	.87	.92	1.00	1.00	1.00	1.00	1.00
spectral2	.99	.97	.99	.98	1.00	1.00	1.00	1.00	1.00	.98	.90
walktrap_GLASSO_ebic	.56	.99	.79	.77	.53	.53	.56	.93	.96	.97	.97
walktrap_GLASSO_ric	.41	1.00	.70	.71	.54	.61	.69	.75	.76	.79	.79
walktrap_mb_ric	.41	1.00	.69	.71	.54	.59	.69	.75	.77	.78	.79
walktrap_tiger_ric	.00	.84	.42	.42	.42	.43	.43	.43	.42	.42	.41
zero_leiden	.73	.97	.92	.78	.50	.87	.89	.91	.93	.92	.92
zero_louvain	.72	.97	.92	.77	.50	.86	.89	.90	.93	.92	.92
zero_walktrap	.76	.96	.92	.80	.50	.86	.93	.94	.95	.93	.91

Table 11. Average Accuracy by Condition

Algorithmic Approach	Scaling		Distribution		Factor Number						
	Ipsatized	Standardized	Equal	Pareto	2	3	4	5	6	7	8
ap	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fa_geominq	.00	.00	.00	.00	.01	.00	.00	.00	.00	.00	.00
fa_none	.00	.00	.00	.00	.01	.00	.00	.00	.00	.00	.00
fa_oblimin	.00	.00	.00	.00	.01	.00	.00	.00	.00	.00	.00
fa_varimax	.00	.00	.00	.00	.01	.00	.00	.00	.00	.00	.00
hdbscan	.87	1.00	.98	.89	1.00	1.00	1.00	1.00	1.00	.81	.75
leiden_GLASSO_ebic	.59	.96	.81	.74	.54	.51	.54	.95	.98	.97	.93
leiden_GLASSO_ric	.35	.96	.72	.60	.50	.52	.63	.71	.74	.77	.74
leiden_mb_ric	.28	.97	.67	.58	.48	.51	.58	.66	.70	.72	.72
leiden_tiger_ric	.00	.94	.49	.44	.45	.46	.47	.48	.49	.47	.46
Louvain_GLASSO_ebic	.58	.95	.80	.72	.54	.50	.54	.95	.97	.95	.91
Louvain_GLASSO_ric	.35	.96	.72	.60	.50	.52	.63	.71	.74	.77	.74
Louvain_mb_ric	.29	.97	.67	.59	.48	.51	.58	.67	.70	.73	.73
Louvain_tiger_ric	.00	.93	.49	.44	.45	.47	.47	.48	.49	.47	.46
mg	.56	1.00	.86	.70	.50	.50	.75	1.00	1.00	.87	.84
nbclust_average_kl	.56	1.00	.81	.75	.51	1.00	1.00	.75	.72	.74	.75
nbclust_ward.d_db	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
nbclust_ward.d_kl	.92	1.00	1.00	.92	1.00	1.00	1.00	1.00	1.00	.87	.84
pc_geominq	.00	.00	.00	.00	.01	.00	.00	.00	.00	.00	.00
pc_none	.00	.00	.00	.00	.01	.00	.00	.00	.00	.00	.00
pc_oblimin	.00	.00	.00	.00	.01	.00	.00	.00	.00	.00	.00
pc_varimax	.00	.00	.00	.00	.01	.00	.00	.00	.00	.00	.00
spectral1	.86	1.00	.93	.93	.75	.75	1.00	1.00	1.00	1.00	1.00
spectral2	.98	.93	.98	.93	1.00	1.00	1.00	1.00	1.00	.99	.72
walktrap_GLASSO_ebic	.58	.97	.81	.75	.58	.52	.54	.93	.96	.97	.94
walktrap_GLASSO_ric	.22	.98	.63	.57	.53	.53	.58	.65	.64	.65	.62
walktrap_mb_ric	.21	.99	.63	.57	.52	.51	.57	.64	.65	.67	.66
walktrap_tiger_ric	.00	.93	.47	.46	.48	.48	.47	.48	.48	.44	.41
zero_leiden	.73	.85	.94	.65	.57	.96	.86	.83	.84	.77	.70
zero_louvain	.71	.85	.93	.63	.56	.96	.86	.82	.83	.75	.68
zero_walktrap	.87	.83	.99	.71	.95	.89	.90	.88	.86	.78	.71

Table 12. Average MAE by Condition

	Scaling		Distribution		Factor Number						
Algorithmic Approach	**Ipsatized**	**Standardized**	**Equal**	**Pareto**	**2**	**3**	**4**	**5**	**6**	**7**	**8**
ap	8.19	8.13	8.38	7.93	9.47	8.24	7.74	8.08	7.99	7.94	7.63
fa_geominq	5.27	3.33	4.22	4.37	2.17	3.03	3.75	4.39	4.98	5.61	6.14
fa_none	5.27	3.33	4.22	4.37	2.17	3.03	3.75	4.39	4.98	5.61	6.14
fa_oblimin	5.27	3.33	4.22	4.37	2.17	3.03	3.75	4.39	4.98	5.61	6.14
fa_varimax	5.27	3.33	4.22	4.37	2.17	3.03	3.75	4.39	4.98	5.61	6.14
hdbscan	0.41	0.00	0.02	0.40	0.00	0.00	0.00	0.00	0.00	0.19	1.25
leiden_GLASSO_ebic	1.72	0.06	0.91	0.87	0.94	2.10	2.95	0.08	0.03	0.04	0.12
leiden_GLASSO_ric	2.41	0.05	1.22	1.23	2.51	2.12	1.28	0.72	0.69	0.57	0.70
leiden_mb_ric	3.18	0.05	1.62	1.61	2.86	2.85	1.78	1.15	0.97	0.86	0.83
leiden_tiger_ric	4.99	0.10	2.51	2.58	1.07	1.55	2.05	2.53	3.00	3.54	4.06
louvain_GLASSO_ebic	1.71	0.08	0.91	0.88	0.95	2.06	2.90	0.08	0.04	0.06	0.15
louvain_GLASSO_ric	2.36	0.05	1.19	1.22	2.5	2.02	1.24	0.71	0.68	0.57	0.70
louvain_mb_ric	3.09	0.05	1.58	1.56	2.87	2.77	1.66	1.10	0.95	0.83	0.82
louvain_tiger_ric	4.99	0.10	2.51	2.59	1.08	1.55	2.06	2.53	3.00	3.54	4.05
mg	0.51	0.00	0.22	0.30	0.75	0.50	0.25	0.00	0.00	0.13	0.16
nbclust_average_kl	0.59	0.00	0.26	0.33	0.74	0.00	0.00	0.25	0.28	0.55	0.25
nbclust_ward.d_db	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
nbclust_ward.d_kl	0.17	0.00	0.00	0.17	0.00	0.00	0.00	0.01	0.00	0.26	0.32
pc_geominq	5.27	3.33	4.22	4.37	2.17	3.03	3.75	4.39	4.98	5.61	6.14
pc_none	5.27	3.33	4.22	4.37	2.17	3.03	3.75	4.39	4.98	5.61	6.14
pc_oblimin	5.27	3.33	4.22	4.37	2.17	3.03	3.75	4.39	4.98	5.61	6.14
pc_varimax	5.27	3.33	4.22	4.37	2.17	3.03	3.75	4.39	4.98	5.61	6.14
spectral1	0.35	0.00	0.21	0.14	0.49	0.74	0.00	0.00	0.00	0.00	0.00
spectral2	0.05	0.29	0.07	0.27	0.01	0.00	0.00	0.00	0.00	0.10	1.07
walktrap_GLASSO_ebic	1.89	0.05	0.97	0.97	0.91	2.30	3.24	0.14	0.05	0.06	0.10
walktrap_GLASSO_ric	3.42	0.04	1.69	1.77	3.7	2.66	1.66	1.03	0.98	0.98	1.10
walktrap_mb_ric	4.35	0.04	2.16	2.23	4.44	4.16	2.12	1.34	1.11	1.09	1.09
walktrap_tiger_ric	4.99	0.12	2.53	2.58	1.05	1.56	2.08	2.52	3.01	3.56	4.11
zero_leiden	0.29	0.34	0.06	0.56	0.43	0.04	0.16	0.24	0.24	0.45	0.65
zero_louvain	0.32	0.34	0.08	0.58	0.45	0.04	0.16	0.25	0.26	0.47	0.67
zero_walktrap	0.20	0.43	0.01	0.62	0.09	0.11	0.14	0.21	0.28	0.54	0.84

Table 13. Average MBE by Condition

	Scaling		Distribution		Factor Number						
Algorithmic Approach	**Ipsatized**	**Standardized**	**Equal**	**Pareto**	**2**	**3**	**4**	**5**	**6**	**7**	**8**
ap	8.19	8.13	8.38	7.93	9.47	8.24	7.74	8.08	7.99	7.94	7.63
fa_geominq	5.27	3.33	4.22	4.37	2.17	3.03	3.75	4.39	4.98	5.61	6.14
fa_none	5.27	3.33	4.22	4.37	2.17	3.03	3.75	4.39	4.98	5.61	6.14
fa_oblimin	5.27	3.33	4.22	4.37	2.17	3.03	3.75	4.39	4.98	5.61	6.14
fa_varimax	5.27	3.33	4.22	4.37	2.17	3.03	3.75	4.39	4.98	5.61	6.14
hdbscan	-0.41	0.00	-0.02	-0.4	0.00	0.00	0.00	0.00	0.00	-0.19	-1.25
leiden_GLASSO_ebic	1.50	-0.02	0.78	0.7	0.28	2.09	2.94	0.04	-0.02	-0.04	-0.12
leiden_GLASSO_ric	2.13	0.00	1.11	1.02	2.20	1.96	1.16	0.64	0.55	0.44	0.51
leiden_mb_ric	2.95	0.04	1.50	1.49	2.54	2.70	1.72	1.10	0.87	0.80	0.73
leiden_tiger_ric	-4.99	0.10	-2.49	-2.41	-0.92	-1.45	-1.94	-2.47	-2.98	-3.45	-3.93
louvain_GLASSO_ebic	1.47	-0.03	0.77	0.68	0.30	2.06	2.9	0.04	-0.03	-0.06	-0.13
louvain_GLASSO_ric	2.08	0.00	1.07	1.01	2.20	1.85	1.11	0.62	0.54	0.44	0.51
louvain_mb_ric	2.87	0.04	1.46	1.45	2.56	2.62	1.6	1.05	0.85	0.77	0.72
louvain_tiger_ric	-4.99	0.10	-2.49	-2.4	-0.92	-1.45	-1.93	-2.47	-2.98	-3.45	-3.94
mg	0.35	0.00	0.22	0.13	0.75	0.5	0.25	0.00	0.00	-0.13	-0.16
nbclust_average_kl	0.26	0.00	0.26	0.01	0.74	0.00	0.00	0.24	0.28	-0.28	-0.06
nbclust_ward.d_db	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
nbclust_ward.d_kl	0.01	0.00	0.00	0.01	0.00	0.00	0.00	-0.01	0.00	-0.26	0.32
pc_geominq	5.27	3.33	4.22	4.37	2.17	3.03	3.75	4.39	4.98	5.61	6.14
pc_none	5.27	3.33	4.22	4.37	2.17	3.03	3.75	4.39	4.98	5.61	6.14
pc_oblimin	5.27	3.33	4.22	4.37	2.17	3.03	3.75	4.39	4.98	5.61	6.14
pc_varimax	5.27	3.33	4.22	4.37	2.17	3.03	3.75	4.39	4.98	5.61	6.14
spectral1	0.35	0.00	0.21	0.14	0.49	0.74	0.00	0.00	0.00	0.00	0.00
spectral2	-0.04	-0.29	-0.07	-0.26	0.01	0.00	0.00	0.00	0.00	-0.10	-1.07
walktrap_GLASSO_ebic	1.68	-0.04	0.84	0.80	0.26	2.28	3.21	0.07	0.01	-0.01	-0.08
walktrap_GLASSO_ric	3.15	0.00	1.57	1.58	3.40	2.50	1.52	0.95	0.85	0.86	0.94
walktrap_mb_ric	4.12	0.03	2.04	2.11	4.13	4.00	2.05	1.28	1.02	1.02	1.01
walktrap_tiger_ric	-4.99	0.12	-2.47	-2.41	-0.95	-1.44	-1.91	-2.49	-2.97	-3.44	-3.88
zero_leiden	-0.05	-0.34	0.06	-0.44	0.43	-0.04	-0.16	-0.24	-0.24	-0.45	-0.65
zero_louvain	-0.06	-0.34	0.05	-0.45	0.45	-0.04	-0.16	-0.25	-0.26	-0.47	-0.67
zero_walktrap	-0.12	-0.43	0.01	-0.56	0.09	-0.07	-0.10	-0.20	-0.27	-0.54	-0.83

Introduction (Study 2B)

The primary subject of interest is the number of factors in data from Saucier & Goldberg (1996) as identified using the approaches previously validated in the preceding study. Substantive comparison of these new findings with the findings from Saucier & Goldberg is also of interest (i.e., it would still be noteworthy if each produced different five-factor solutions). It was previously demonstrated that the often-termed "clustering" algorithms (though factor analysis can be used in clustering) which are more common to data/computer science outperformed methods more common to psychology for data like that of Saucier & Goldberg (1996). This effect was largely driven by Saucier & Goldberg's reliance on ipsatization although variable size was also impactful, albeit by necessitating more efficient operations and precluding valid but computationally inefficient ones.

Methods

Data

The data in these analyses will be the ratings of 435 trait-descriptive adjectives by two combined samples (*n*=899) of undergraduate and law students at a western United States university (Saucier & Goldberg, 1996). These ratings were combined from 507 self- and 392 peer ratings. 636 of the responses were on a 7-step scale, with the remaining 263 on an 8-step scale. These data are ipsatized.

Dimension Detection and Interpretation

In Study 2A, I demonstrated that performance on identifying factor number (accuracy) and substantive item-factor assignment (ARI) were not perfectly related in the ipsatized condition. Therefore, algorithms were selected for their performance on each.

Algorithms in the ipsatized condition with accuracy greater than 80% were selected to identify the factor number, and algorithms with an ARI greater than .80 were selected to identify to content of those factors.

Factor number

Algorithms selected to identify the number of factors were Ward's minimum variance with Davies-Bouldin index, average linkage with both Davies-Bouldin and Krzanowski-Lai indices, Spectral clustering (both methods), and HDBSCAN. The walktrap method on the zero-order correlation matrix was included as a secondary, exploratory approach, as it performed well but considerably lower than the optimal algorithms.

Factor Content

Algorithms selected to identify factor content were Ward's minimum variance with both Davies-Bouldin and Krzanowski-Lai indices (Ward D-B and Ward K-L), average linkage with Krzanowski-Lai indices (Average K-L), Spectral clustering (Spectral 1 and Spectral 2), and gaussian mixture modeling (mclust).

Results

Factor Number

Results of the factor estimates of the chosen algorithms are below (Table 14). Overall, a solution with two factors is effectively the consensus.

Table 14. Factor estimates across algorithmic approaches

Algorithm	Factor Estimate	Cluster Sizes
HDBSCAN	3	169, 65, 5 (169 unassigned)
Spectral Clustering (Method 1)	2	259, 176
Spectral Clustering (Method 2)	2	259, 176
Ward's Method with D-B Index	2	223, 212
Ward's Method with K-L Index	2	223, 212
Average Linkage with K-L Index	4	224, 209, 1, 1

Zero Walktrap	3	122, 103, 210

There is some superficial disagreement among factor estimates. However, examination of Ward's Method with K-L Index revealed two one-item clusters, and HDBSCAN revealed that almost half (196) of the terms were unclustered, with clusters being 169, 65, and 5 terms in size. The walktrap method on the zero-order correlation matrix is effectively the lone dissenter, with three clusters of 122, 103, and 210 terms.

Factor Content

Algorithms selected to identify factor content were gaussian mixture modeling, Spectral clustering, Ward's minimum variance with Davies-Bouldin index, and average linkage with both Davies-Bouldin and Krzanowski-Lai indices. Adjusted Rand Index of each pairwise clustering is presented to demonstrate agreement where present (Table 15).

Table 15. Pairwise ARI of algorithmic solutions

	mclust	Spectral 1	Spectral 2	Ward D-B	Ward K-L	Average K-L
mclust	1.00	.23	.23	.26	.26	.27
Spectral 1	.23	1.00	1.00	.67	.67	.59
Spectral 2	.23	1.00	1.00	.67	.67	.59
Ward D-B	.26	.67	.67	1.00	1.00	.82
Ward K-L	.26	.67	.67	1.00	1.00	.82
Average K-L	.27	.59	.59	.82	.82	1.00

As is clear, the gaussian mixture model from *mclust* had minimal overlap with partitions from the other algorithms, which largely agreed with each other. Also notable, there is strong inter-method congruence: both spectral methods produced identical solutions, as did both indices within Ward's method. All *NbClust* solutions were strongly congruent. A table of cluster partitions can be found in the appendix (Table 48).

The substantive content of these two clusters were socially desirable (e.g., affectionate, humorous, pleasant, versatile) and socially undesirable (e.g., callous, fearful, unintelligent, sedate, unsophisticated). Of these ten pairings (excluding all *mclust*) pairings, around 20-30 of the 435 terms were not placed in the same clusters. Thus, while this solution itself has minimal theoretical import, it garnered empirical consensus. The impact of social desirability on responding is well-understood but is not considered to be a personality trait per se. This finding highlights the need to anticipate and account for social desirability, at least within these data.

The Zero/Walktrap combined approach was not initially used for factor interpretation, given its comparatively low ARI. However, investigation into its solution revealed a three-factor solution similar to the Big Five factors of Agreeableness, Conscientiousness, and Extraversion/Openness.

Discussion

The most noteworthy observation to carry from the first of these studies is that in the absence of ipsatization, all dimension assessment approaches perform well. In the case of dealing with non-ipsatized data, it is easier to disregard a few approaches than to develop a hierarchy of approaches. As in Study 1, unrotated factors/components are not advisable; while EFA/PCA tended to over-factor generally, items did not load strongly onto those factors/components post-rotation. Affinity propagation also did not perform well. The EBICGLASSO-based approaches outperformed alternative regularization schemes. Thus, the same recommendations in Study 1 apply: either exploratory graph analysis (easily implemented with *EGAnet*) or a rotated factor model based on factors selected by parallel analysis or *fspe*. Empirically, factors and components performed equivalently, and so the theoretical justification for factors over components (i.e., using shared variance) is enough to prefer them.

While there is a wide gap between the maximum of 40 variables considered in Study 1 and the 435 variables considered in Study 2, if the same patterns of performance persist in those margins, psychologists need not deviate from their preferred analytic approach between exploratory factor analysis or exploratory graph analysis. Rather than developing a faculty for these various tools, researchers would be better off focusing their efforts to conceptualizing their response generating process, as these tools may identify a structure that is difficult to reconcile against a mis-specified theoretical process (e.g., a probable social desirability factor rather than trait factors). For handling ipsatized data, the clustering approaches (minus affinity propagation) were appreciably better than the rest. However, ipsatization is a data pre-processing step that, given these findings, should be validated. The current study calls that validity into question but was not aimed at that determination and does not constitute an adequate test of validity. Even in the case that aggregating data on different scales is necessary, item-level standardizing did not threaten factor recoverability in this simulation and should be preferred until further investigation. If clustering is not a desirable method to researchers handling ipsatized data, it should be noted that the community detection algorithms applied to the unregularized correlation matrices were effective for all but the two-factor structures.

The meaning of the finding that terms can be broadly categorized as socially desirable or socially undesirable is ambiguous: this has been discussed as a substantive factor (De Raad et al., 2010; De Raad & Barelds, 2008), but also as a responding artifact. Further study could disentangle these possibilities.

The decision by Saucier & Goldberg (1996) to ipsatize participants' responses complicates assessment of the dimensionality of their data. Ipsatizing is not without benefit; primarily, it controls for individual response styles or a common factor and allows for datasets using different scales to be combined. This minimizes idiosyncratic response styles but can reduce between-group bias (e.g. if one group is more modest or extreme in their responding style). There may be other shared sources of variance removed by ipsatizing.

However, ipsatizing forces a respondent's items to sum to zero, which can induce negative covariances among items and ultimately alter the factor structure (Rudnev, 2021). As well, if there is a substantive between-person general dimension (e.g., positivity or social desirability), that factor would be lost. As well, the absolute size of eigenvalues is decreased, which could impact dimension detection in algorithms using eigenvalues as a criterion. On the other hand, standardizing variables to combine datasets on different scales was demonstrated empirically to allow for more effective recovery of the true factor structure on the data simulated here.

Based on these results, traditional clustering algorithms outperform factor analytic and network-based methods on ipsatized data à la Saucier and Goldberg (1996). However, this finding should be tempered regarding generalizability for psychology, as such high-dimensional data are comparatively rare. Moreover, the high error from factor analytic methods was driven by weak, superfluous factors that few terms strongly loaded onto. While this is problematic in a large simulation study where substantive interpretation is infeasible, in the more typical case of factoring few datasets this does not prevent an issue. Therefore, in the (admittedly unusual) event that other researchers are handling similar (but non-ipsatized data), most dimension detection approaches would suffice.

These findings demonstrate the inherent difficulty in dimension reduction work: such works recover clusters based on an implicit theoretical construct of a cluster. The choice of clustering approach—and parameters within a chosen approach—allows for numerous, perhaps equally defensible solutions. However, there may be reason to hope for a reaching an analytically-consensual structure. The finding of three factors from the walktrap method is especially intriguing, since it mirrors the result of a natural language investigation by Cutler & Condon (2022), suggesting that there are substantive factors within these data awaiting recovery by a valid dimension detection approach (made all the more difficult by their ipsative nature).

Most importantly, this work demonstrates (albeit through its own failure) that attempting to select a model (such as clustering algorithms operationalize models of clusters) based on empirical tests on data simulated from a generative model will fail if that generative model does not align with the true model. Yet, eschewing such tests only allows a researcher to remain ignorant of this possibility.

Future Directions

Goldberg (1990) demonstrated the invariance of the Big Five structure to choice of factor extraction and rotation method. While laudable, considering this study those methods appear less heterogeneous—and therefore a less stringent test—than the wider selection of algorithms designed with a similar intent. When identifying factor number is a substantive portion of a research endeavor, simulating data could serve as a power analysis or method selection step. There are numerous methods not considered in this work that can identify factors in data, including: stochastic block modeling (Abbe, 2018), Ricci flow (Ni et al., 2019), topological data analysis (Aktas et al., 2019), various machine learning algorithms (Milano et al., 2024), and innumerable other clustering algorithms.

There are two main directions based on these findings. The first is to identify a non-ipsatized dataset which would allow a wider range of factoring approaches as well as improved validity therein. The second is to account for this general factor of social desirability and build a more holistic model of responses. As before, this could be accomplished through a simulation study in which some proportion of terms within factors are given negative loadings on that factor. Dimension detection could be performed as before; as well, a general factor could be extracted first and dimension detection performed on the residuals. Ideally, these two directions would be undertaken in parallel, allowing for both improved data and methodological quality.

Chapter 4: Study 3

Introduction

The goal of Study 3 is to address the limitations of Study 2. As noted, there were two primary issues: first, the ipsative data were sub-optimal for factoring; second the selected method for factoring identified non-personological structure in the data. Given the difficulty in factoring ipsatized data, similar non-ipsative data were identified to be used in these analyses. These data come from the Eugene-Springfield Community sample (Goldberg, 2018) and include 1,128 responses to 360 personality terms. They are publically available on Harvard Dataverse.

As was previously demonstrated, careful attention must be paid to the data-generating model to select an approach capable of estimating its constituent components or at least one capable of identifying the components of interest. In other words, if responses to terms were reflective of their respondents' trait levels and social desirability, for a psycholexical investigation it would suffice to use an algorithm that could only identify all relevant traits or both identify the trait and social desirability components but not solely social desirability, as seemed to be the case in the last study. Selecting the proper approach to do so through simulation starts with selecting a better generative model.

To better approximate responding to trait descriptive adjectives, additional data-generating characteristics should be considered. Based on the past study, the most obvious additional factor is the social desirability of traits. This would be modeled as a general orthogonal factor. Another would be term familiarity (modeled as difficulty). Although excluding terms based on lack of familiarity is a good and common practice in psycholexical investigations, familiarity does vary across terms. For instance, in Saucier & Goldberg (1996), terms were rated from 0 (no knowledge of that term) to 9 (a rater would use to describe someone extremely often) and terms below a mean of 3.25 would be excluded. The basis for this cutoff is unclear; more importantly, such a low cutoff would likely admit terms that many respondents rarely use. This is especially likely since we expect variance around the mean which could allow a sizeable minority to provide a very low response (i.e., 0-2) without depressing the mean below 3.25. At such a low cutoff, floor effects would also be likely for difficult items, which would entail positive skew, increasing the mean above the median, further exacerbating the problem. Next, because gender effects have been shown to systematically vary across factors, this variability should also be included in the simulation. Last, the amount of skew in distributions of responses should be varied across terms, reflecting variability in difficulty and entropy. These appear to be reasonable and sufficient additions to more realistically simulate psycholexical data.

Study 3A

Methods

Generating Mechanism

To assess performance of these various algorithms, datasets were simulated using a Monte Carlo design in which seven parameters in the data generative process were systematically varied and equally sampled with a similar approach to past works in this vein (Garrido et al., 2016; H. Golino et al., 2020). These parameters (Table 16) included number of factors, items per factor imbalance, sample size, response option number (categories), general factor loading, group factor loading, and total number of items.

Table 16. Systematically Varied Generative Parameters

Condition	**Levels**
Number of factors	2,3,4,5,6,7,8
Items per factor imbalance	Equally or Exponentially distributed
Sample size	500, 1000, 2000

Categories	5, 6, 7, 8, 9
General factor loading	U(0,.2); U(.2,.4); U(.3,.5); U(0,.5)
Group factor loading	U(.2,.7); U(.5,.7); U(.3,.65)
Total items	330, 435, 1000

All combinations of levels were included, with the exception that for 1,000 total items, only a sample size of 2,000 was considered. Therefore, there were 5,880 possible combinations, which was replicated 10 times for a total of 58,800 observations.

The rationale behind the levels for number of factors or item/factor imbalance was the same as the previous study. Categories were chosen based on the wide range of response options in published datasets—the dataset analyzed here uses a 9-option response scale. General factor loading was chosen to represent four levels of strength: small and narrow, relatively small and narrow; strong and narrow, and wide.

Group factor loadings were similarly chosen: .30-.65 is a common finding (Saucier & Goldberg, 1996); .50-.70 is a strong, specific range; and .20-.70 is slightly more permissive than the usual finding.

Additional parameters were varied across simulations. These parameters include gender proportion, proportion of negatively loading general factor terms, proportion of negatively loading group factor terms, proportion of cross-loading terms, effect size of gender on responding, number of factors impacted by gender, skew, proportion of skewed variables, proportion of difficult variables, difficulty of difficult variables, and proportion of respondents affected by difficult variables (skewed). These variables and their distributions can be found in the table below (Table 17). These variables were randomly sampled as they were empirically demonstrated to be less impactful, and the combinatorial explosion of equally sampling all parameters would be intractable to study.

Table 17. Non-Systematically Varied Generative Parameters

Condition	**Levels**
Gender proportion	Beta(15, 15)
Number of Factors impacted by gender	0, 1, 2, 3
Gender effect size	U(.1, .3)
Proportion of negatively loading general factor items	U(.33-.66)
Proportion of negatively loading group factor items	U(.33-.66)
Proportion of cross-loading items	U(0, .2)
Skew	Gamma(1, 2); Gamma(2,3); Gamma(3,4)
Proportion of skewed variables	U(0, .66)
Difficult variables	U(0., .3)
Difficulty of difficult variables	1, 2, 3
Proportion of skewed respondents	U(0, 1)

The gender proportion was set to produce a mean of 50% with a standard deviation of approximately 10%. The proportion of negatively loading items was set to allow a wide range of possible loadings. Past research has tended to find relatively low cross-loading items; this parameter was slightly larger than that, with the intention of producing conservative estimates on performance, as cross-loadings are a clear threat to clustering. The proportion of skewed variables and the extent of skewness were similarly intended as a stress-test of clustering performance, although in practice term responses tend to be skewed. Last, the difficulty and the proportion of difficult variables was intended to operationalize and test the impact of the observation that terms in lexical research—being selected by a post-graduate researcher but administered to (frequently) undergraduates—may often not be well-understood, and therefore difficult to endorse. All code can be found online at https://osf.io/36wn7/.

Clustering algorithms

All clustering algorithms from Study 2 were considered. As in that study, the *fspe* and *EGAnet* protocols were to slow for inclusion, although the EBICGLASSO approach (approximating EGAnet for factor sizes greater than one) was used. Given the size of the datasets simulated and the number of combinations per iteration, this process was computationally expensive and several concessions needed to be made to run in a tractable amount of time.

By far the most impactful decision was to generate a small subset (1,000) of possible datasets and exclude the worst-performing algorithms on those datasets. Hierarchical clustering (through *NBClust*), gaussian mixture modeling (*mclust*), parallel analysis, spectral clustering, and Fisher's R-to-Z transform were excluded based on these preliminary findings. Although this was a small dataset, their average accuracy and ARI was approximately zero—with the exception of the R-to-Z transform, which was excluded because it frequently encountered issues inverting the covariance matrix and was still markedly worse than the included approaches.

The included approaches were community detection algorithms (Leiden, Louvain, and Walktrap) on the zero-order correlation matrix, and those same community detection algorithms on the EBICGLASSO and adaptive lasso regularized networks. While these approaches were considerably better than the rest, their average ARI was around .60, which was low to be considered compelling evidence of their applicability to a new, empirical dataset.

Extraction of the general factor

Preliminary testing indicated that the general factor strength was the variable with the greatest impact on performance, followed by group factor strength and factor number. This positions the issue as a signal detection problem, in which the general factor represents noise to the group factors' signal. Therefore, removing the general factor without using a priori knowledge of this factor was a primary consideration of this work and required extensive piloting. Early in testing it was identified that the zero-order community detection performed best when residualizing the first PC under a moderate general factor. Hypothesizing that under a weaker general factor, the first PC would represent a substantive trait and not general factor, an additional step was taken to attempt to algorithmically identify the general factor. A Schmid-Leiman transform with a factor estimate from the highest performing dimensionality algorithm was tested but proved computationally inefficient and less effective than other tested approaches. The ultimate approach used was to extract the first ten principal components, estimate a distribution of loadings, then identify the component with the most loadings above a set percentile. This percentile was identified through tuning on 1,000 simulated datasets, which identified both .40 and .50 as the cutoff for loading proportion as 100% accurate, and both .30 and .60 as upwards of 95% accurate. A final percentile cutoff of .45 was used. When applying this residualizing approach to the adaptive lasso, an error was produced by the nearly singular covariance matrix. Both adding a small ridge coefficient or a Ledoit-Wolf transform solved this but did not improve the effectiveness of the adaptive lasso. However, using the EBICGLASSO estimate for the covariance matrix was highly effective and therefore was used as the initial estimate for the adaptive lasso.

The choice of EBIC value was determined by tuning the eBIC parameter γ across values of 0.0, 0.1, and 0.2 on simulated datasets. It showed a monotonic decrease in performance as EBIC increased. An EBIC value of zero was selected for the full simulation study. BIC was used for the adaptive lasso, which is identical to the eBIC when $\gamma = 0$.

It was also noted that deskewing variables slightly improved performance and was used in these analyses. This was done by calculating skewness by variable, identifying variables with skewness with a z-score greater than six, and applying a rank-based normal transformation to those variables. The same measure of performance in the last studies were used.

Computational Aspects

All data generation and analyses were performed using R Version 4.4.1 (R Core Team, 2022). Regularization was done using the *GGMncv* package (version 2.1.1; D. Williams, 2020). Walktrap, Leiden, and Louvain community detection algorithms were run with the *igraph* package (version 2.1.1; Csárdi et al., 2024). Adjusted Rand Index was calculated using the *mclust* package (version 6.0.1; Scrucca et al., 2023).

Results

Results (Table 18) demonstrated that for accuracy, EBICGLASSO regularization on deskewed, residualized data was the most effective approach, although the zero-order and adaptive lasso correlation were also highly effective. All algorithms were similarly capable in terms of ARI.

Table 18. Performance on bifactor data

Algorithmic Approach	n	Accuracy	MAE	MBE	ARI	Over/Under Factored?
Zero_leiden	58800	.83 [.83, .83]	.29 [.28, .29]	-.24 [-.25, -.23]	.88 [.88, .89]	Under
Zero_louvain	58800	.83 [.82, .83]	.29 [.29, .3]	-.24 [-.25, -.24]	.88 [.88, .89]	Under
Zero_walktrap	58800	.76 [.76, .77]	.42 [.41, .43]	-.33 [-.33, -.32]	.87 [.86, .87]	Under
adapt_bic_leiden	58800	.83 [.82, .83]	.33 [.32, .34]	.33 [.32, .33]	.88 [.88, .88]	Over
adapt_bic_louvain	58800	.82 [.82, .83]	.34 [.33, .34]	.33 [.32, .34]	.88 [.88, .88]	Over
adapt_bic_walktrap	58800	.84 [.84, .85]	.31 [.3, .32]	.31 [.3, .32]	.89 [.89, .89]	Over
EBICGLASSO_leiden	58800	.87 [.86, .87]	.25 [.24, .26]	.19 [.18, .2]	.90 [.89, .90]	Over
EBICGLASSO_louvain	58800	.86 [.86, .86]	.26 [.25, .27]	.19 [.18, .2]	.89 [.89, .90]	Over
EBICGLASSO_walktrap	58800	.87 [.87, .87]	.26 [.25, .27]	.17 [.16, .18]	.90 [.90, .90]	Over

Note 5. Zero, adapt_bic, and EBICGLASSO refer to zero-order, adaptive lasso with BIC information criterion, and EBICGLASSO means of estimating a network. Leiden, Louvain, and walktrap are the community detection methods applied.

Because of the number of parameters included in these analyses, only one- and two-way interactions were tested. Two-way interactions were minimal in all approaches (see heatmaps in appendices; Table 49-Table 52). Variance explained by factor number was high in all outcomes and all approaches. ARI improved as factor number increased. The zero-order approaches showed accuracy decreasing as a function of factor number, while the other approaches showed the opposite.

Variance explained by general factor loading strength was moderate for accuracy and ARI in the EBICGLASSO and zero-order approaches. All approaches broadly had a minimum for the general loading range of 0-.50, with the exception that the Leiden and Louvain algorithms in the zero-order network case performed worst in the general factor loading range of 0-.20. Plots below illustrate these findings (Figure 34, Figure 35, Figure 36, Figure 37).

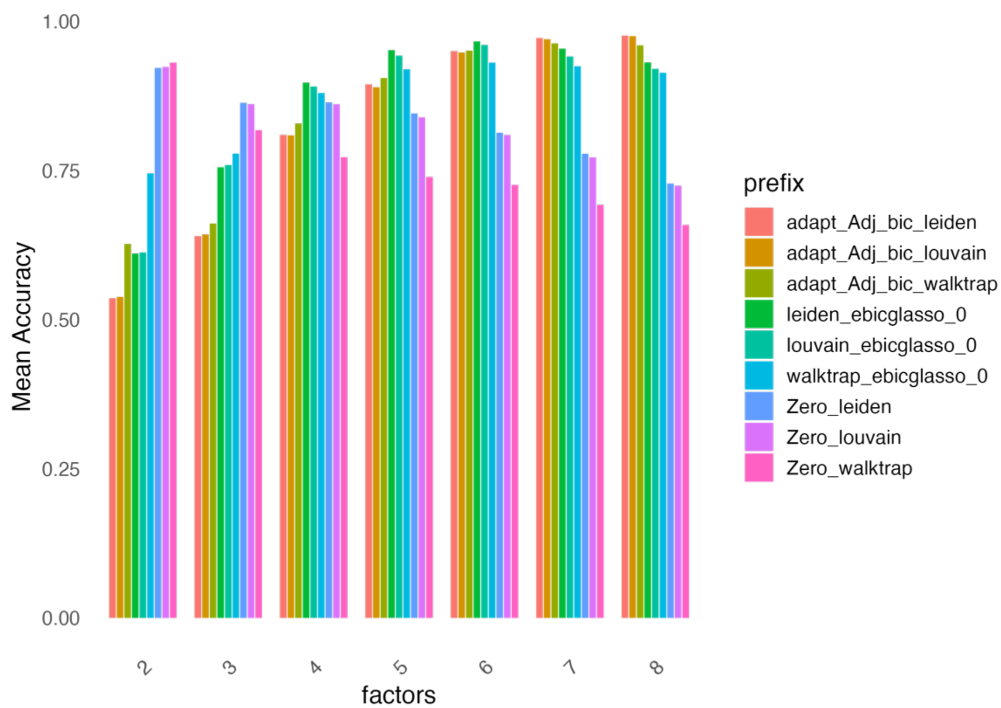

Figure 34. Accuracy of Algorithmic Approaches across Factor Levels

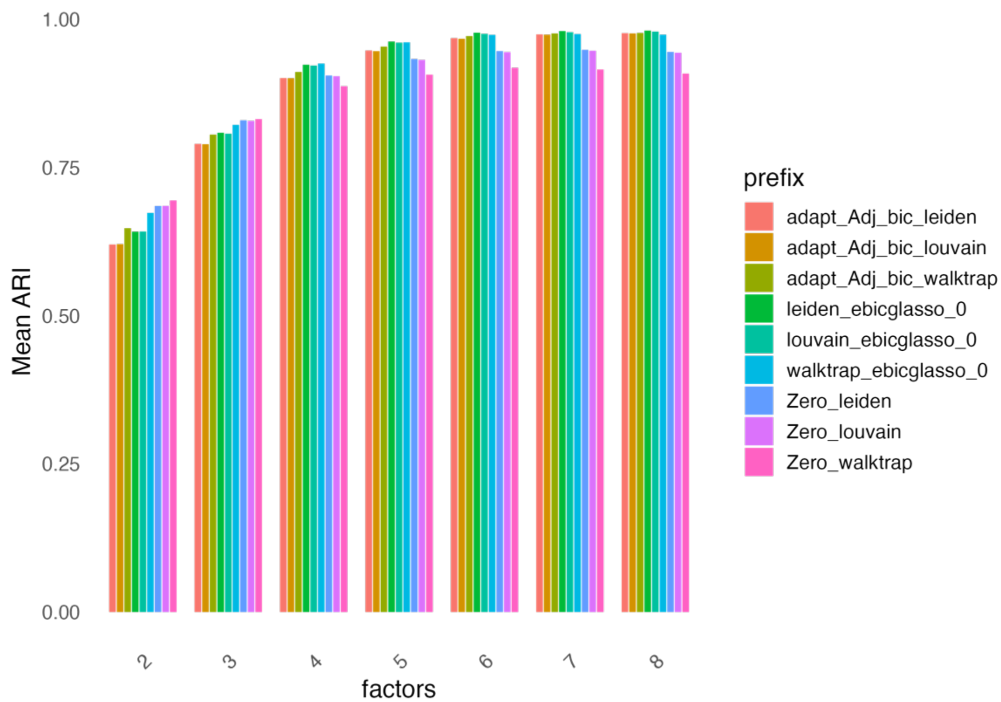

Figure 35. ARI of Algorithmic Approaches across Factor Levels

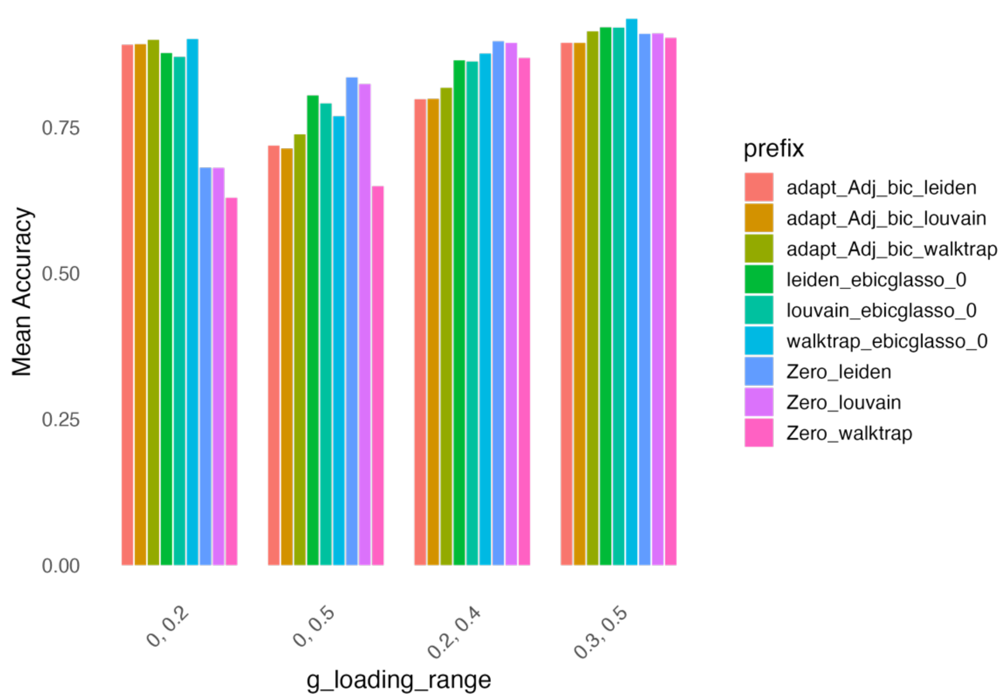

Figure 36. Accuracy of Algorithmic Approaches across General Factor Loading Ranges

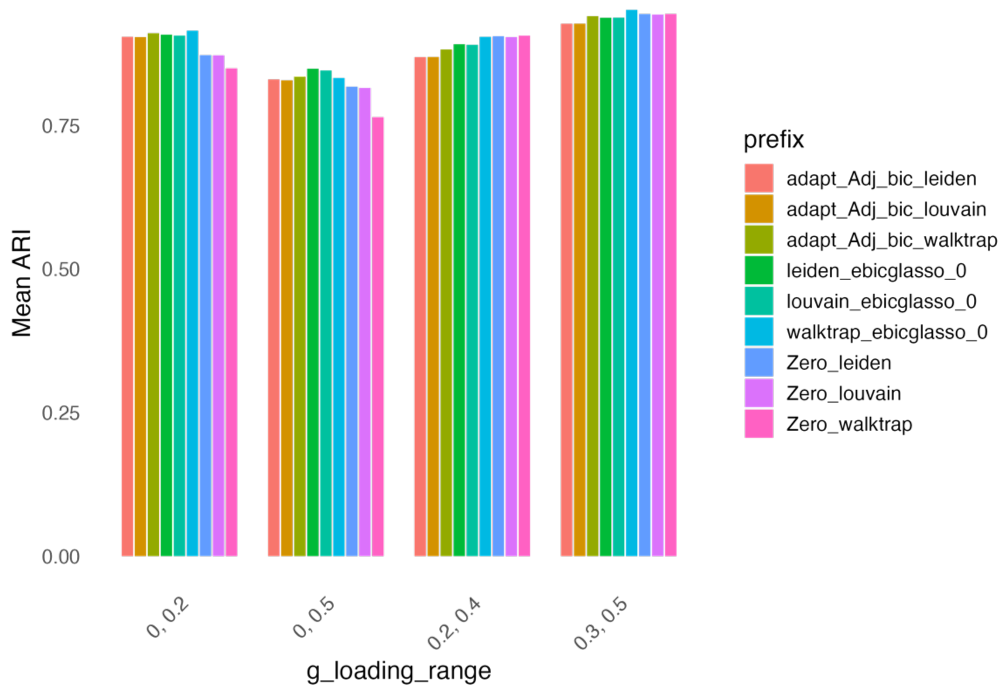

Figure 37. ARI of Algorithmic Approaches across General Factor Loading Ranges

Overall, ARI was good (greater than .75) for all approaches except the two-factor case. The general factor most strongly impaired factor detection in the 0-.50 case. Differences in community detection algorithm (Louvain, Leiden, Walktrap) were minimal. Overall, these findings demonstrate that all approaches were satisfactory.

Stability Analyses

One important caveat with the community detection algorithms tested is that the Louvain and Leiden algorithms introduce randomness in identifying their partitions (the Walktrap algorithm is wholly deterministic). Although it was just empirically demonstrated that these algorithms are highly effective in identifying the most central items in simulated data and generally effective at identifying the number of clusters, it is possible for different iterations to produce different partitions. The extent to which this is relevant, especially for these data, is unclear. On a related note, the stability of a solution on a subset of data is unclear (effects of sample size notwithstanding).

To assess these unknowns, another simulation study similar to the previous one was conducted in which data were simulated from a subset of the previous conditions. A table of conditions is below (Table 19). Notable exclusions are all categories but 8 (as this is ultimately how the empirical data are scaled), all total items but 345 (adjusted to be similar to the empirical data), and the U(0, .2) general factor loading (not empirically justified). All non-systematically varied parameters remain the same as in the previous section (Table 17).

Table 19. Systematically Varied Generative Parameters

Condition	Levels
Number of factors	2,3,4,5,6,7,8
Items per factor imbalance	Equally and Exponentially distributed
Sample size	1000
Categories	8
General factor loading	U(.2,.4); U(.3,.5); U(0,.5)
Group factor loading	U(.2,.7); U(.5,.7); U(.3,.65)
Total items	345

For each simulated dataset, bootstrapped Leiden and Louvain algorithms (on zero-order, adaptive lasso, and EBICGLASSO-regularized correlation matrices) were conducted 50 times on 85% of simulated rows of data (resampled each time), developing a final partition identified by hierarchically clustering a matrix of the percent of times each pairwise term combination appeared in the same partition. Terms that are more strongly linked will occur in the same cluster more often. Applying different thresholds as a requirement for the percentage of time terms need to appear together to be included in a cluster produces different partitions. Naturally, as the threshold increases, clusters will be smaller and many.

In preliminary testing, excluding regularized methods (to decrease computation time), thresholds between .20 and .40 showed similar accuracy, although all thresholds between .10 and .90 had a similar ARI. This latter finding is unsurprising, as the higher the threshold, the more clusters will be identified, and these clusters will be more strongly intercorrelated. The final simulation study used a more restricted range of cut threshold, including .20, .40, and .60.

Results demonstrate that all methods produce a valid clustering by ARI (Table 20). However, the eBIC and adaptive lasso regularized methods tend to identify more clusters than the non-regularized methods (demonstrated by their high MBE) because of the relative instability of low-strength edges and subsequently less-smooth topography induced by regularization. For a high-bandwidth, low trait number solution, this makes the regularized approaches less appealing, although their high ARI necessitated them being tested. The highest accuracy was by median and modal factor number estimates from community detection from the zero-order correlation matrices.

Table 20. Stability Analysis of Bootstrapped Approaches

Regularization	Community Algorithm	Threshold	n	Accuracy	MAE	MBE	ARI
Zero-order	Leiden	0.6	635	.72	0.67	0.36	.89
Zero-order	Louvain	0.6	635	.7	0.75	0.43	.88
Zero-order	Leiden	0.4	635	.86	0.27	-0.17	.88
Zero-order	Louvain	0.4	635	.86	0.27	-0.16	.88
Zero-order	Leiden	0.2	635	.87	0.26	-0.22	.88
Zero-order	Louvain	0.2	635	.86	0.27	-0.23	.88
Adaptive Lasso	Leiden	0.2	635	.45	5.95	5.95	.87
Adaptive Lasso	Louvain	0.2	635	.45	5.92	5.92	.87
Adaptive Lasso	Leiden	0.4	635	.45	6.29	6.29	.87
Adaptive Lasso	Louvain	0.4	635	.44	6.38	6.38	.86
Adaptive Lasso	adaptLeiden	0.6	635	.43	8.21	8.21	.86
Adaptive Lasso	adaptLouvain	0.6	635	.43	8.29	8.29	.86
EBICGLASSO	ebicLouvain	0.2	635	.38	14.87	14.82	.85
EBICGLASSO	ebicLeiden	0.2	635	.37	14.86	14.82	.85
EBICGLASSO	ebicLeiden	0.4	635	.36	15.26	15.22	.84
EBICGLASSO	ebicLouvain	0.4	635	.36	15.17	15.13	.84
EBICGLASSO	ebicLeiden	0.6	635	.34	16.45	16.43	.84
EBICGLASSO	ebicLouvain	0.6	635	.34	16.5	16.49	.84
Zero	Leiden (median)	0.2	635	.88	0.24	-0.19	

Zero	Leiden (median)	0.4	635	.88	0.25	-0.19
Zero	Leiden (median)	0.6	635	.88	0.25	-0.19
Zero	Leiden (mode)	0.2	635	.88	0.24	-0.19
Zero	Leiden (mode)	0.4	635	.88	0.25	-0.19
Zero	Leiden (mode)	0.6	635	.88	0.25	-0.19
Zero	Louvain (median)	0.2	635	.88	0.24	-0.19
Zero	Louvain (median)	0.4	635	.88	0.25	-0.19
Zero	Louvain (median)	0.6	635	.88	0.24	-0.19
Zero	Louvain (mode)	0.2	635	.88	0.24	-0.2
Zero	Louvain (mode)	0.4	635	.88	0.25	-0.19
Zero	Louvain (mode)	0.6	635	.88	0.24	-0.19
Adaptive Lasso	Louvain (mode)	0.6	635	.51	0.73	0.73
Adaptive Lasso	Leiden (median)	0.2	635	.5	0.73	0.73
Adaptive Lasso	Leiden (median)	0.6	635	.5	0.74	0.73
Adaptive Lasso	Leiden (mode)	0.2	635	.5	0.73	0.73
Adaptive Lasso	Leiden (mode)	0.4	635	.5	0.74	0.73
Adaptive Lasso	Leiden (mode)	0.6	635	.5	0.73	0.73
Adaptive Lasso	Louvain (median)	0.2	635	.5	0.74	0.74
Adaptive Lasso	Louvain (median)	0.6	635	.5	0.74	0.74
Adaptive Lasso	Louvain (mode)	0.2	635	.5	0.74	0.73
Adaptive Lasso	Louvain (mode)	0.4	635	.5	0.73	0.73
Adaptive Lasso	Leiden (median)	0.4	635	.49	0.74	0.74
Adaptive Lasso	Louvain (median)	0.4	635	.49	0.74	0.74
EBICGLASSO	Leiden (median)	0.4	635	.43	0.7	0.65
EBICGLASSO	Leiden (median)	0.6	635	.43	0.7	0.65
EBICGLASSO	Leiden (mode)	0.2	635	.43	0.7	0.66
EBICGLASSO	Leiden (mode)	0.4	635	.43	0.7	0.65
EBICGLASSO	Leiden (mode)	0.6	635	.43	0.7	0.66
EBICGLASSO	Louvain (median)	0.6	635	.43	0.7	0.66
EBICGLASSO	Louvain (mode)	0.4	635	.43	0.7	0.66
EBICGLASSO	Louvain (mode)	0.6	635	.43	0.7	0.65
EBICGLASSO	Leiden (median)	0.2	635	.42	0.7	0.66
EBICGLASSO	Louvain (median)	0.2	635	.42	0.71	0.66
EBICGLASSO	Louvain (median)	0.4	635	.42	0.7	0.66
EBICGLASSO	Louvain (mode)	0.2	635	.42	0.7	0.65

Overall, these findings demonstrate the efficacy of community detection algorithms in identifying the number of factors in data generated from relatively complex mechanisms. However, the need to identify and residualize a general factor is yet another reminder that factor detection is not an automatic, thoughtless endeavor, but operationalize a test of underlying assumptions of data which merits recognition.

Study 3B

This study aims to provide a re-analysis similar to study 2B, having identified the optimal approaches to factoring data simulated with higher verisimilitude, then applying those approaches to non-ipsative data. That previous study demonstrated that the Louvain and Leiden algorithms produced valid partitions on regularized and non-regularized data. Crucially, regularization caused solutions of a high factor number. These solutions would identify the largest core cluster of a partition, with related but distinct items forming their own smaller clusters. Non-regularized solutions would tend to find larger, fewer clusters with overall weaker average intracorrelations. Although this latter solution is generally what is understood to constitute a Big Few model of personality, both approaches will be tested as they may each have some insight to be gleaned and should have similarities. These approaches will be applied to a different set of trait-descriptive adjectives, which were selected for their relatively high sample size and non-ipsative nature.

Methods

These data come from the Eugene-Springfield Community sample (Goldberg, 2018) include 1,128 responses (56.9% female) to 360 personality terms. These data were collected in 1993 in the U.S. Pacific Northwest (Eugene-Springfield). These data and additional demographics are published on Harvard Dataverse. Notably, this sample is overwhelmingly (98.4%) Caucasian.

Item responses are on a 9-point scale where 1 indicates *Extremely inaccurate* and 9 indicates *Extremely accurate*. However, a 5 is used to indicate *Uncertain or the meaning of the* *term is unclear*. Visual inspection of item histograms suggested a low proportion of fives, especially considering it approximated the mean response of most items. Thus, all responses for a five were removed for later imputation, and all responses above a five were decreased by one, to make the scale range from 1-8. As well, terms with greater than 15% responses as five were dropped (n=15) on the basis that they were not well understood. By similar logic, respondents who endorsed a five on more than 10% of terms (n=87) were dropped. Given that factor analytic methods struggle with missingness, respondents with more than three missing items (n=39) were dropped, with the remainder of blanks imputed using the *mice* package (Buuren & Groothuis-Oudshoorn, 2011). In total, 2.8% of total responses were imputed, the vast majority of which (98.3%) were originally a five.

The psychometric validity of using a mid-point to indicate uncertainty by design is questionable. Although raters appeared to underreport 5s, a logistic regression of term order of the included terms in the survey versus probability of endorsing a 5 was run to assess whether participants may have forgotten the special instruction for five as they progressed through the survey. The logistic regression model was statistically significant, $\chi^2(1) = 144.06$, $p < .001$. The model revealed a significant positive relationship between adjective order and the probability of receiving a rating of 5 ($b = 0.0006$, $SE = 0.00007$, $z = 12.00$, $p < .001$, 95% CI [0.0007, 0.001]). While this effect appears small per individual position, adjectives in the final position had approximately 1.24 times higher odds of receiving a rating of 5 compared to adjectives in the first position. However, predicted rates ranged from 3.9% to 4.6% across the first and tenth deciles, demonstrating a low base rate. To avoid overly manipulating data, they were not adjusted to account for this finding.

Although a social desirability factor is common across psycholexical investigations, the presence of one in these data was assessed empirically using both spectral clustering and the principal components loading approach previously detailed.

The Leiden and Louvain median cluster estimates from the zero-order correlation matrix had the highest accuracy among the bootstrapped algorithms, both generally and for the case when the general factor loading was between 0 and .5. Thresholds of .2 and .4 performed best, although .6 was not appreciably worse and was also included for consideration. The Leiden and Louvain on the EBICGLASSO-regularized and zero-order correlation matrix derived networks performed equivalently and were used for substantive interpretation. Software used did not deviate from the first part of this study.

Results

The first principal component was identified as the likeliest candidate for the social desirability component. Analysis of the loadings first principal indicated a strongly platykurtic distribution between -.60 and .60, which is reasonably aligned with the general factor loading condition of a uniform distribution of items from (0, .5), where an item's sign could also be flipped depending on the parameter for proportion of negatively loading items. Spectral clustering of all terms suggested a two-cluster solution based on social desirability. This result mirrors that of the previous study. These findings together lend strong support to the notion that a general factor, namely social desirability, is present and well-identified.

The bootstrapped zero-order community detection algorithms produced five factors as a median and modal estimate. Of those five, the three large factors seen (Figure 38, Figure 39) corresponded roughly to dynamism/surgency (e.g., vigorous, ambitious, crafty, strong-willed), social-regulation (e.g., pleasant, considerate, immature, sympathetic) and openness (e.g., philosophical, old-fashioned, inquisitive, unreflective), with smaller factors of conscientiousness (e.g., sloppy, perfectionistic, thorough) and expressiveness (e.g., timid, sedate, chatty, theatrical). In the previous study, the Leiden and Louvain algorithms on the zero-order correlation matrices had, respectively, an accuracy of .89 and .87, and ARI of .95 and .94.

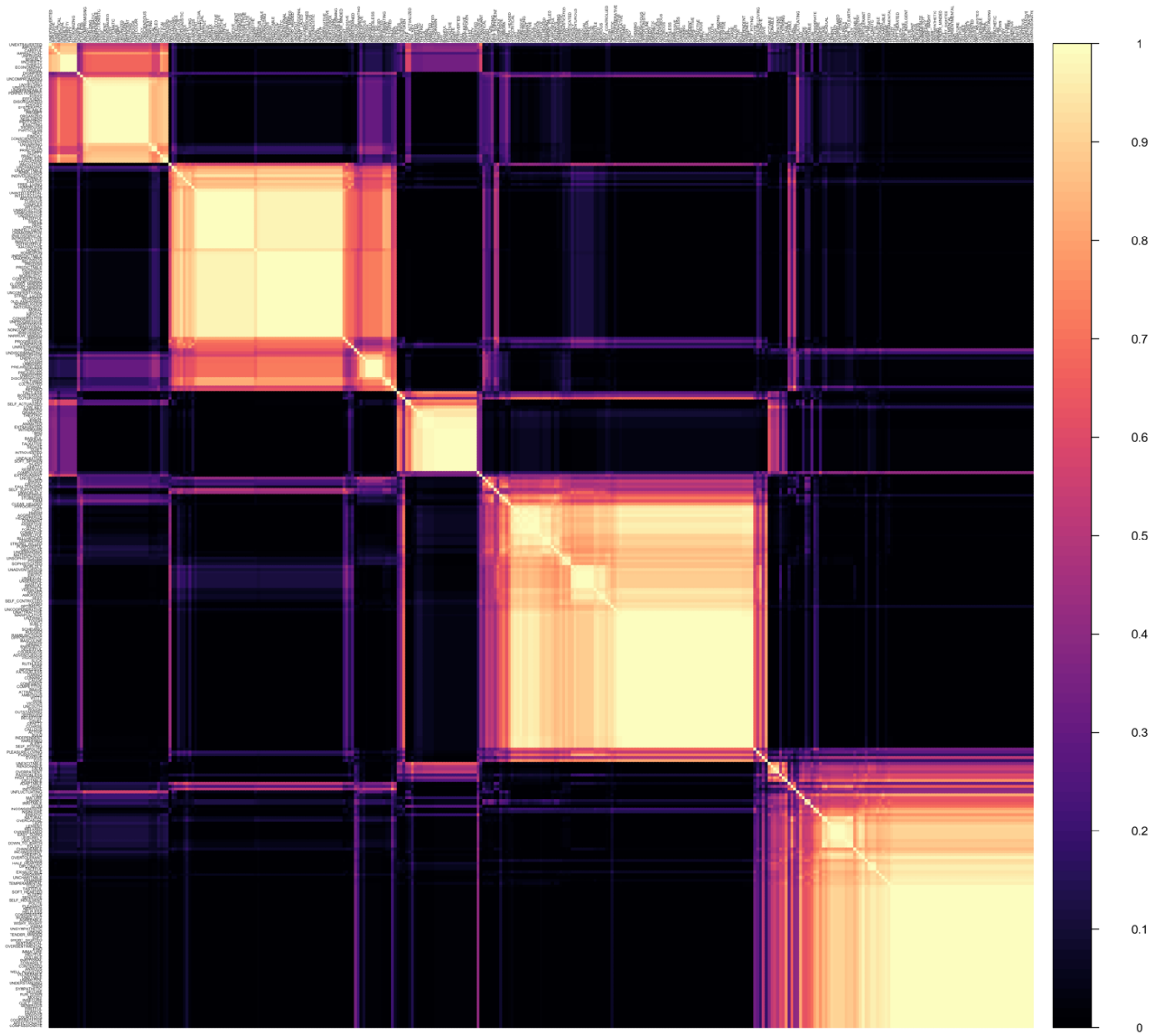

Figure 38. All Terms Clustered by Bootstrapped Leiden/Louvain on Zero-Order Correlation

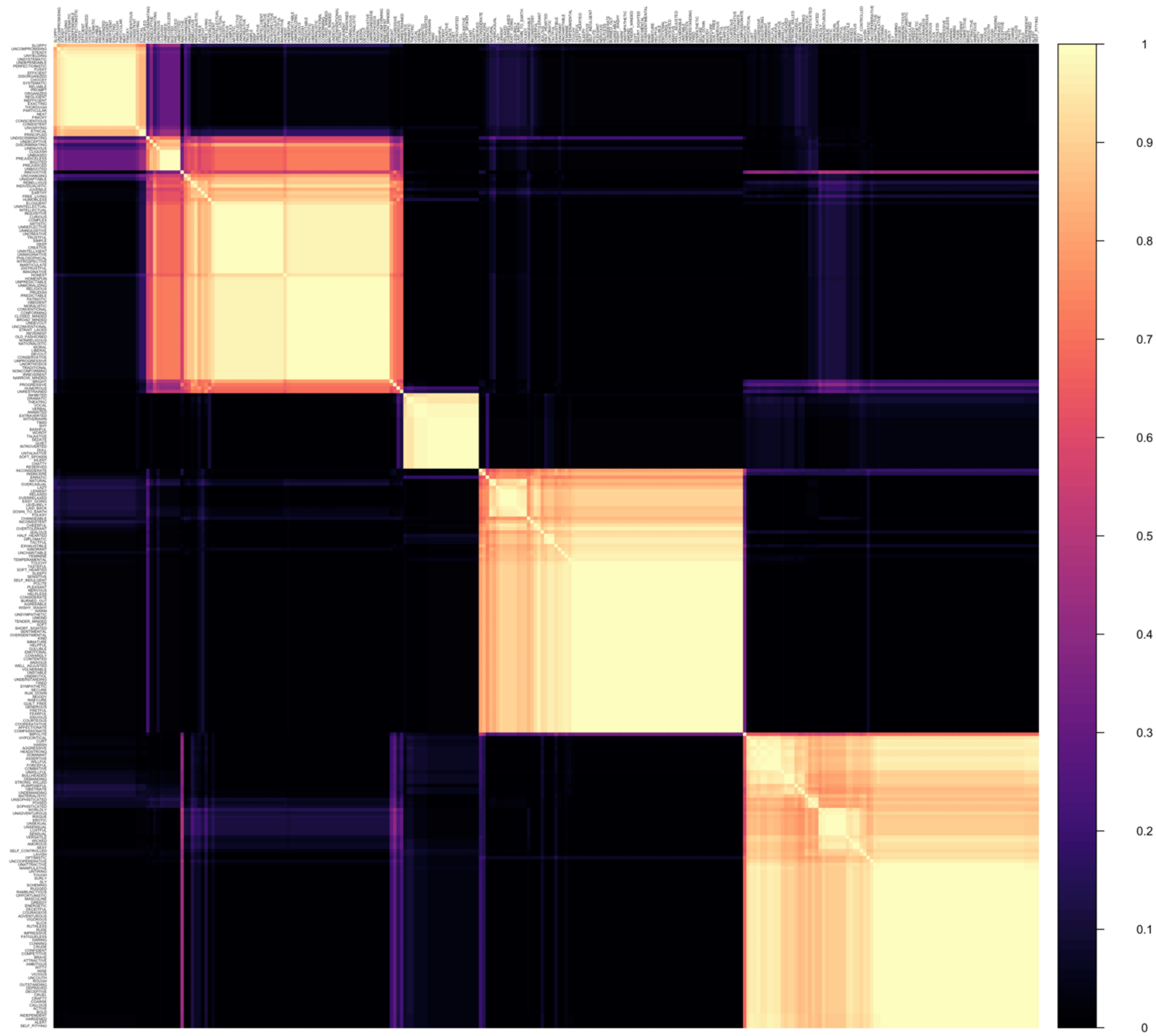

Figure 39. Terms Assigned to Clusters of Size Greater than 10 by bootstrapped Leiden/Louvain on Zero-Order Correlation

The bootstrapped EBICGLASSO algorithms produced 8 clusters as a median solution. However, visual inspection reveals the same three primary factors (Figure 40, Figure 41). Dynamism and Social regulation (both having 43 items) remain the largest clusters. Furthermore, there is a more obvious cleaving in openness (43 items) between conforming (e.g., patriotic, obedient, rebellious) and intellectual openness (e.g., deep, creative, imaginative). Conscientiousness (18 items) and expressiveness (23 items) are recovered as before. There is also an overt sexuality factor (12 items; e.g., sexy, risqué, passionless) and casualness factor (13 items; e.g., earthy, easy-going, laid-back). In the zero-order structure the sexuality factor was found in the dynamism trait in the zero-order structure, and casual in the social regulation trait.

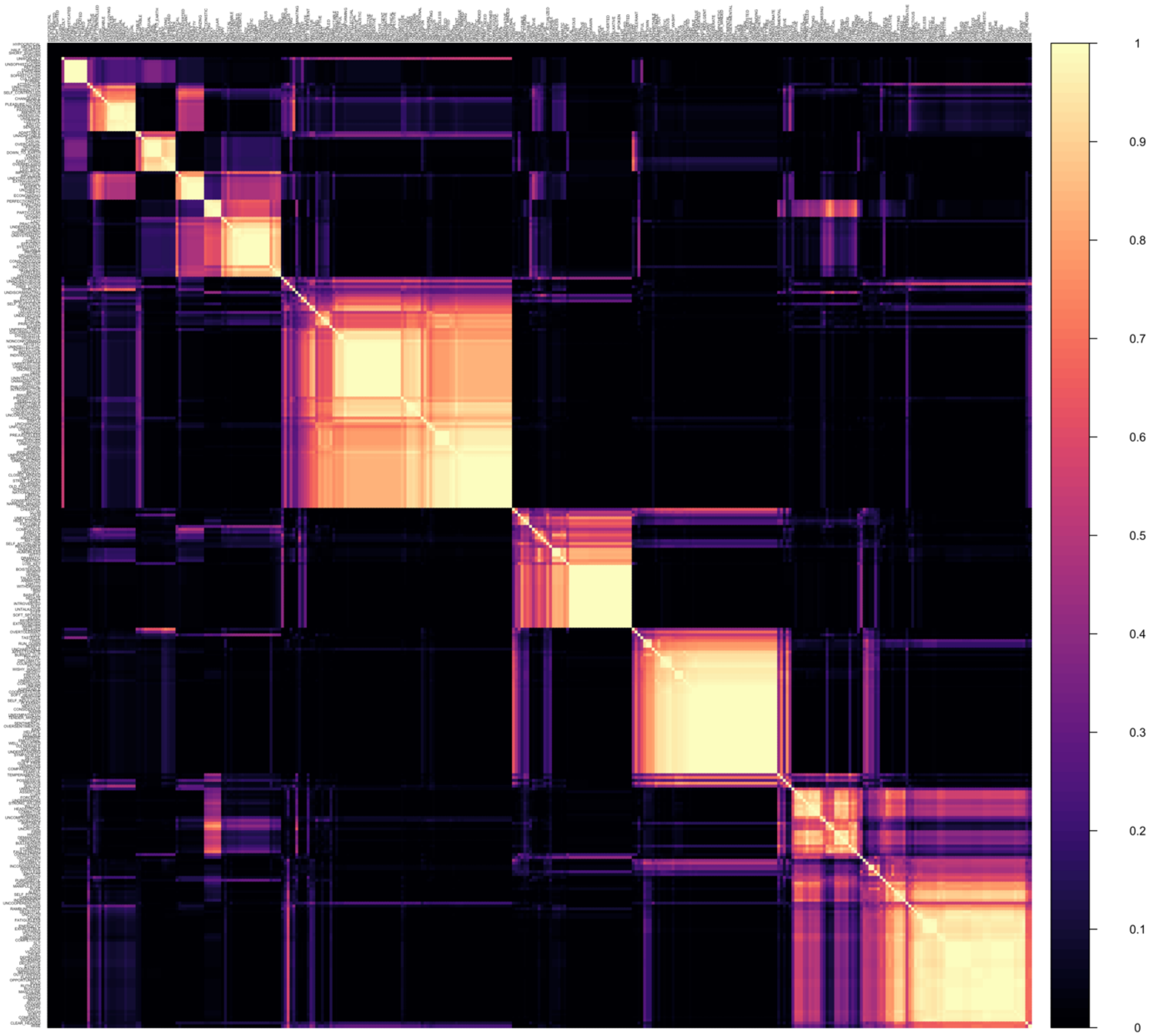

Figure 40. All Terms Clustered by Bootstrapped EBICGLASSO Leiden/Louvain

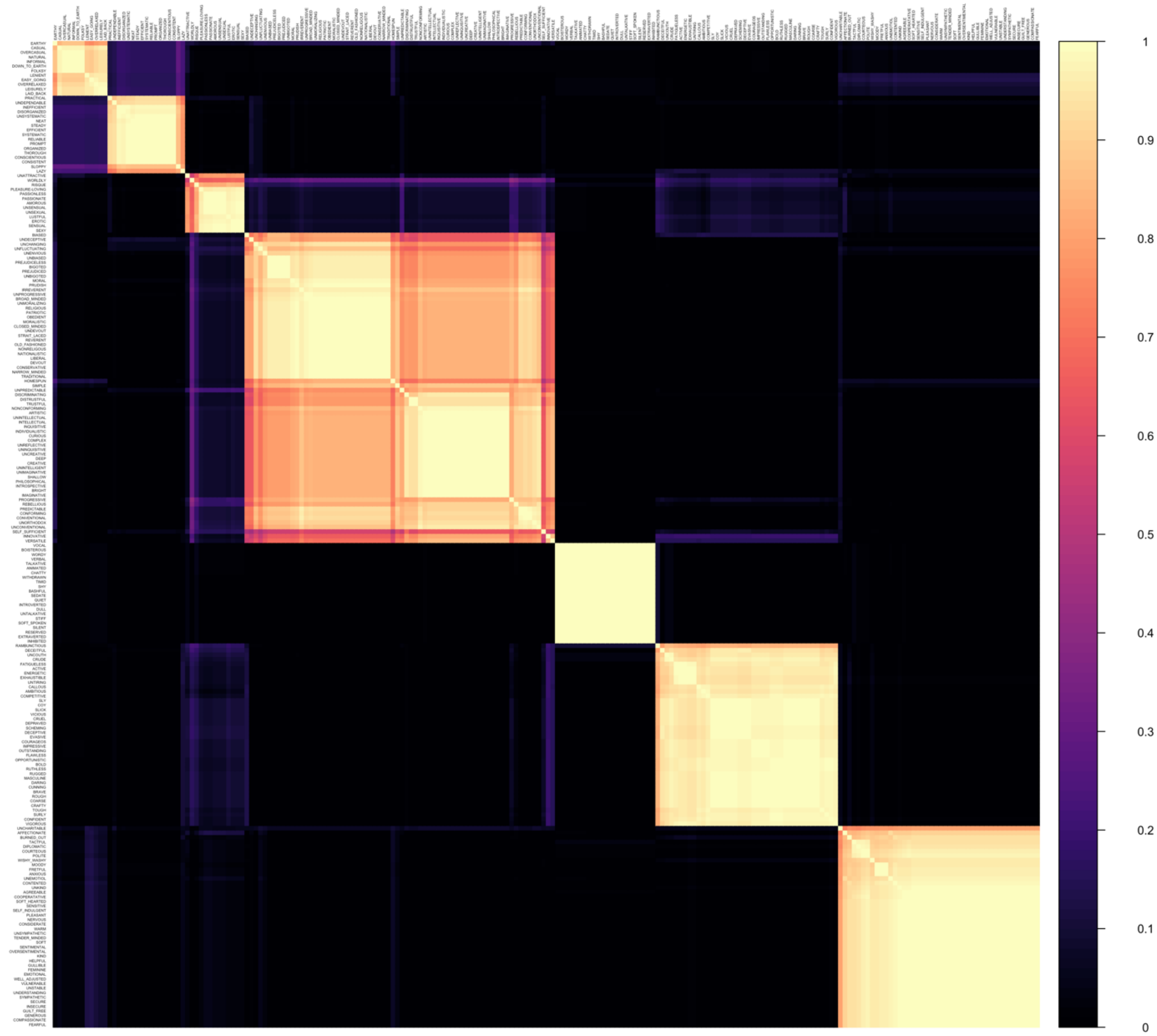

Figure 41. Terms Assigned to Clusters of Size Greater than 10 by Bootstrapped EBICGLASSO Leiden/Louvain

The adaptive lasso algorithms produced, arguably, 9 or 10 clusters (Figure 42, Figure 43). The Louvain algorithm identified 10 clusters as a modal and median solution, and the Leiden algorithm identified 10 as the median and 9 as the mode. Unlike the other two approaches, cluster sizes were more evenly distributed. Again, the largest recognizable trait is openness, which is again split into two clusters: morality/tradition and innovation. The two clusters are joined by an obedience/rebelliousness cluster. The next largest cluster is expressiveness (e.g., *quiet, chatty, boisterous*). Overall, high-bandwidth traits are difficult to identify as the adaptive lasso solution identified smaller, more strongly interrelated terms than the other solutions.

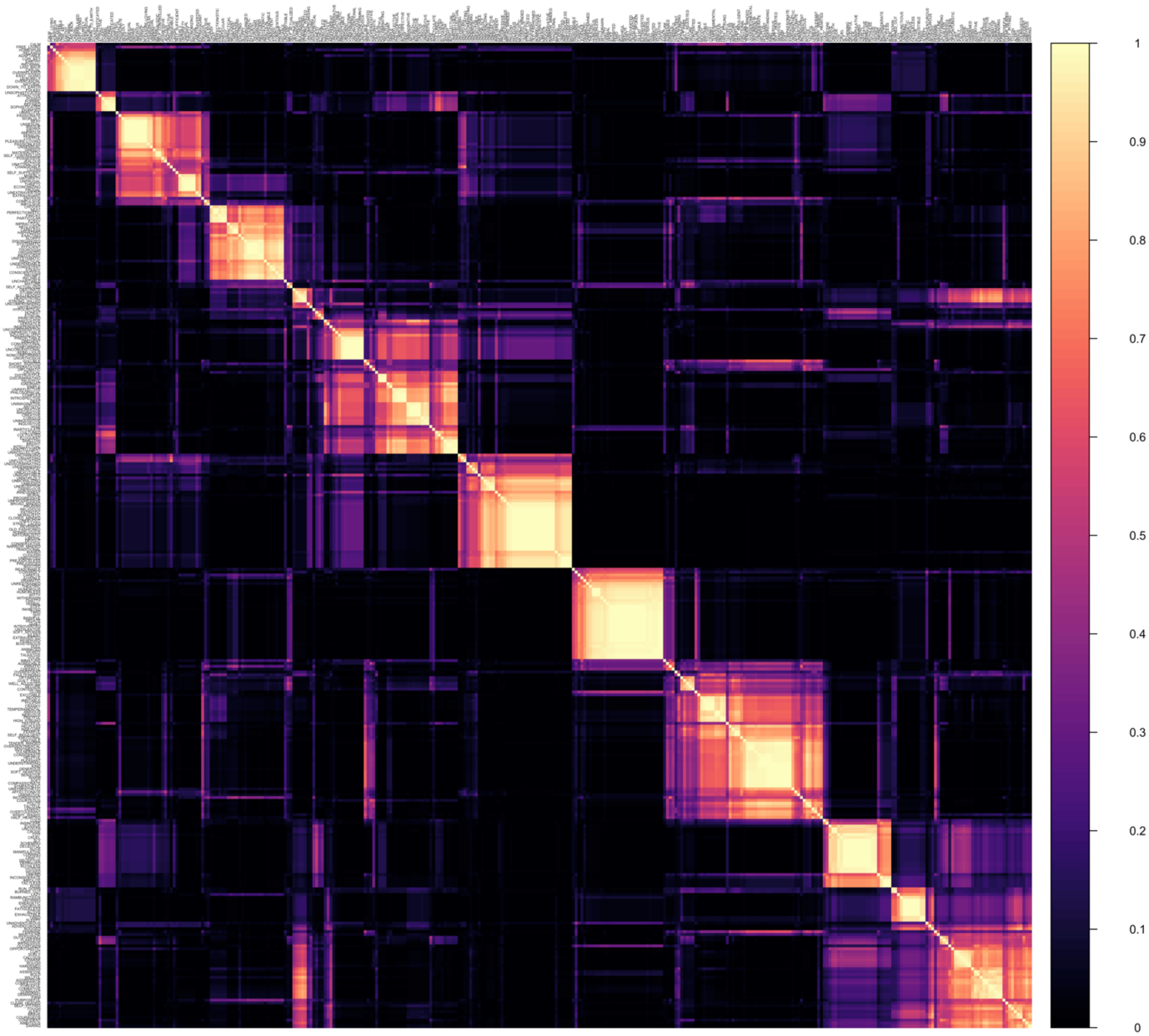

Figure 42. All Terms Clustered by Bootstrapped Adaptive Lasso Leiden/Louvain

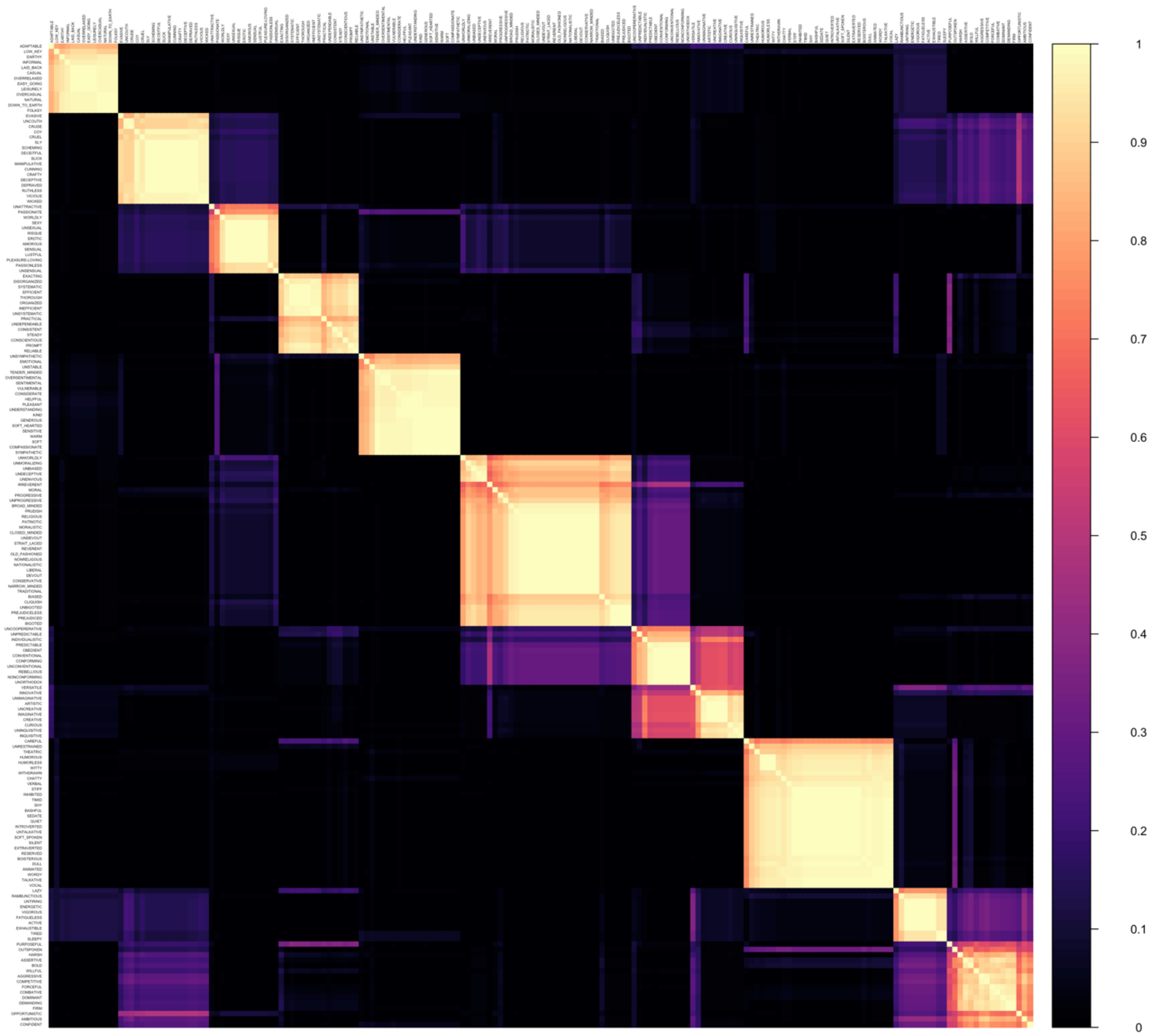

Figure 43. Terms Assigned to Clusters of Size Greater than 10 by Bootstrapped Adaptive Lasso Leiden/Louvain

Agreement of the adaptive lasso with the EBICGLASSO and zero-order solutions was moderate (ARI of .60). When subset to only include the 229 terms that were stably assigned to a cluster in the smaller of the two partitions (the EBICGLASSO-based one), adjusted Rand index was quite high at .82. Therefore, these two solutions agree on a large kernel of the data and less so on smaller clusters. The adaptive lasso solution had an ARI with the EBICGLASSO solution of .42, and .25 with the zero-order solution. When subset to include only stably clustered terms

(206) in the adaptive lasso solution, ARI improved to .75 with the EBICGLASSO solution, and .53 with the zero-order solution. Again, this indicates that all approaches generally agreed on the most central terms but differed on less central ones, with this effect especially pronounced with the adaptive lasso. For a summary of congruence across solutions with all terms included, see Table 21. For congruence of the intersection of terms included across pairs of solutions of large cluster subsets, see Table 22.

Table 21. ARI across Solutions (All Terms)

	Zero-order	EBICGLASSO	Adaptive Lasso
Zero-order	1.00	.60	.25
EBICGLASSO	.60	1.00	.42
Adaptive Lasso	.25	.42	1.00

Table 22. ARI across Solutions (Only Large Cluster Terms)

	Zero-order	EBICGLASSO	Adaptive Lasso
Zero-order	1	.82	.53
EBICGLASSO	.82	1	.82
Adaptive Lasso	.53	.75	1

To test congruence of this solution with the Big Five, an exploratory factor analysis was conducted on the original trait data (Table 53). The highest congruence (still only moderate with an ARI of .44) with the Big Five was on imputed, ipsatized data using varimax-rotated principal component as in past studies (Goldberg, 1990; Saucier & Goldberg, 1996). This was assessed by coding terms based on their highest factor loadings in the factor solution and in Saucier & Goldberg (1996). This disparity is likely due to the sensitivity of factor analytic solutions to their constituent variables—this work used a subset (360 terms) from that 1996 work (435 terms). Parallel analysis suggested 30 factors and 26 components.

When compared to the zero-order, EBICGLASSO, and adaptive lasso solutions, adjusted Rand index was low (.14, .20, and .25, respectively). When terms assigned to clusters outside of the five largest clusters were removed, adjusted Rand index improved but was still low (.43, 36, and .40). Thus, the core five factors identified by clustering and factoring are not congruent.

To further assess correspondence between the EBICGLASSO, adaptive lasso, and zero-order algorithms with the Big Five factor analytic solution, Procrustes rotation analyses were run using Tucker's congruence coefficient and a binary table of cluster assignment as a target matrix.

The Procrustes analysis revealed poor overall congruence between the five-factor EFA solution and the five-cluster zero-order clustering solution (Table 23). The mean optimal congruence across all factor-cluster pairings was .28, which falls well below the threshold for acceptable congruence (.65 and above). Thus, we see little structural correspondence between the two solutions. In familiar terms of ARI, congruence was .24 on all terms and .34 on terms stably clustered in the zero-order solution.

Table 23. Procrustes Congruence of Factor Analytic and Zero-Order Network Factoring

Factor/Cluster	Cluster 1 (Social Regulation; n=61)	Cluster 2 (Openness; n=60)	Cluster 3 (Dynamism; n=54)	Cluster 4 (Intellectual; n=27)	Cluster 5 (Expressive; n=23)
1 (Agreeableness)	**.385**	.081	-.385	.027	.103
2 (Extraversion)	-.058	-.109	**.328**	-.120	-.185
3 (Neuroticism)	-.295	.035	**.306**	.009	-.089
4 (Openness)	.137	.113	**-.158**	.103	-.030
5 (Conscientiousness)	-.155	.031	.082	**.267**	-.053

Tucker's congruence coefficients for the EBICGLASSO solution (Table 24) showed similar performance to the zero-order approaches. However, this solution was based on only half of the variables in the original dataset. Note that much of the openness variables in the cluster solution (e.g., irreverent, unmoralizing, liberal) loaded negatively on conscientiousness in the factor analytic solution (positively loading examples include consistent, organized, and thorough). Openness in the factor analytic solution included broad-minded, imaginative, curious, and narrow-minded (negatively loading). Thus, despite these groups being empirically incongruent, sharing a term seems defensible, and such labels are intended as merely a mnemonic for the set. Congruence in terms of ARI was .20 on all terms and .31 on terms stably clustered in the EBIC solution.

Table 24. Procrustes Congruence of Factor Analytic and EBICGLASSO Network Factoring

Factor/Cluster	Cluster 1 (Dynamism; n=47)	Cluster 2 (Social Regulation; n=47)	Cluster 3 (Openness; n=33)	Cluster 4 (Conscientious; n=25)	Cluster 5 (Expressive; n=24)
1 (Agreeableness)	-.379	**.472**	.076	.021	.079
2 (Extraversion)	**.301**	-.009	-.126	-.047	-.217
3 (Neuroticism)	**.328**	-.172	.068	.044	-.102
4 (Openness)	-.123	.116	**.277**	-.155	-.022
5 (Conscientiousness)	.101	-.077	**.137**	-.037	-.067

Congruence analyses for the adaptive lasso solution (Table 25) were highest at a mean optimal congruence of .37, though overall poor, although note that the five largest clusters produced by the adaptive lasso only summed to 114 total terms. Again, the adaptive lasso did not produce a high-bandwidth solution. Unsurprisingly, the absolute highest congruence is Agreeableness with Kindness, as both overlap on terms such as *compassionate, generous, sympathetic.* The congruence of Conscientiousness with Boldness should not be overinterpreted given the small size of Boldness and that loadings on Conscientiousness were low. However, Conscientiousness in the Big Five has elements stereotypical of maturity that could be taken as assertive, including the terms *firm*, *clear-headed*, and *demanding*. Congruence in terms of ARI was .14 on all terms and .28 on terms stably clustered in the adaptive lasso solution.

Table 25. Procrustes Congruence of Factor Analytic and Adaptive Lasso Network Factoring

Factor/Cluster	Cluster 1 (Conforming; n=32)	Cluster 2 (Expressive; n=30)	Cluster 3 (Kindness; n=20)	Cluster 4 (Machiavellian; n=17)	Cluster 5 (Boldness; n=15)
1 (Agreeableness)	.075	.080	**.553**	-.393	-.360
2 (Extraversion)	-.105	-.130	.079	.130	**.355**
3 (Neuroticism)	.134	-.170	**-.274**	-.010	.156
4 (Openness)	**.349**	-.061	.122	-.026	-.136
5 (Conscientiousness)	.158	-.095	-.224	-.294	**.458**

Partitions generated from all three bootstrapped clustering approaches and the factor analytic assignments can be found in Table 54. It was possible that the clustering solutions were congruent with the Big Five despite this lack of correspondence of cluster partitions with the factor analytic solution usually implemented in recovering the Big Five. This would rely on the factor analytic approach being especially deviant from past solutions but was nonetheless possible. To directly assess congruence between the cluster solutions with the Big Five, the terms from this dataset were sorted into five factors according to their coding in Saucier & Goldberg (1996). Again, congruence was low, even when only comparing the overlap from the Big Five with the five largest clusters in each solution.

Table 26. ARI of Solutions Against the Big Five

	Big Five	**Big Five (Clusters Subset)**
Five Varimax-Rotated Components	.45	.53†
Zero-order	.17	.29
EBICGLASSO	.15	.27
Adaptive Lasso	.12	.25

Note 6. †This subset was based on terms that had an absolute factor loading > .30.

Discussion

All three methods were effective under simulation. In practice, the adaptive lasso produced the most distinct solution. Given this, and the unorthodox usage of the correlation matrix in this field as a similarity measure for community detection, the continued use of EBICGLASSO regularization seems reasonable, especially given the considerable software built around it. This latter approach has also been explored for hierarchical models (Samo et al., 2025) and bifactor structures (Jiménez et al., 2023), though those applications are still cutting-edge .

Bifactor data presented a barrier to factoring. When not accounted for, accuracy and ARI strongly decreased, demonstrating substantively different factor solutions. This is concerning, as bifactor models are common, being both theoretically and statistically sound (A. Rodriguez et al., 2016). These analyses assumed that a bifactor is present; the comparatively poor performance in the weak general factor condition demonstrates the problem of incorrectly making that assumption. Cluster analyses (particularly spectral clustering) were able to identify the bifactor effect, which may represent an avenue to empirical detection of such a model, though this should be studied further. Exploratory bifactor analysis or exploratory graph analysis to identify a bifactor structure (Jiménez et al., 2023) may be similarly fruitful. Although these psycholexically-inspired data are unlike most in psychology, the problematic nature of bifactor structures seems unlikely to be attenuated by smaller variable sets. Ultimately, there may be no replacement for theory and iterative data exploration.

In the previous studies in this work, it was easier to suggest a few approaches to avoid than to choose. However, in this study the exploratory graph approaches were by far the most robust to the bifactor structures in these data, as they had an ARI of around .6 prior to residualizing the general factor. Interestingly, this occurred regardless of the regularization approach used. This may indicate that modularity (the basis for Louvain, Leiden, and Walktrap algorithms) is an effective clustering criterion for psycholexical data. It is further notable that the unregularized networks were an effective basis for community detection, as they did not attempt to limit the number of edges in the network, which is generally a best practice in community detection. However, the theory behind exploratory graph analysis is that communities are identified from variables densely linked by unique covariances (partial correlations) with fewer linkages across communities. Those regularized partial correlations are a crucial aspect of the theory as they represent the variable-level relationships the theory calls for, rather than a common factor model. Though the unregularized networks were effective there are both conceptual (they don't implement the concepts of exploratory graph analysis) and pragmatic (their performance is on par with regularized networks and their full-connectedness is unorthodox) reasons for preferring EBICGLASSO-derived networks. To induce sparsity, thresholds could be applied, though EBICGLASSO accomplishes the same task. The extent to which sparsity among trait adjectives should be expected is variable. It seems more probable that traits are densely, if weakly, connected across communities. However, the common factor model assumption of local independence or a linear item-factors relationship in a Big Few model seems even more of a departure from the ground truth. Neither a common factor nor network psychometric model should be considered "true". However, the considerable noninvariance of personality structures both across demographics (Beck et al., 2023) and at the individual vs. population level (Beck & Jackson, 2020) makes it difficult to conceptualize the trait domains as more than a statistical convenience and therefore better considered a formative, not reflective model. Network psychometrics is a more appealing framework in this light.

It is notable and heartening that of the parameters tested, only factor number and loading strength impacted the performance of clustering, especially as factor number performed worst at 2 factors, which is perhaps too broad to be desirable for most personality structure theorists. Though it is difficult to forecast the performance of models when moving from simulated to empirical data, the complexity of the models being tested represents the most stringent test of factoring algorithms for psycholexical data to date.

These results disagree with the Big Five, especially in the lack of a neuroticism factor, but also shed light on its genesis. Openness—which has typically been found to not replicate across cultures (De Raad et al., 2010)—is clearly recovered in these data. Social regulation and dynamism have essentially been found to replicate across cultures (De Raad et al., 2010), although authors (including this one) label them differently (viz. alpha/beta, agency/communion, and arguably extraversion/agreeableness). Conscientiousness is identifiable as well. Thus, these traits are well-situated within the broader set of personality structures. The presence of a social desirability factor is similarly congruent with past findings (De Raad et al., 2010; De Raad & Barelds, 2008).

There are three primary limitations to this implementation of the lexical postulate. First, the terms included are limited and may not be especially representative of this sample's trait-descriptive lexicon. It is well-known that variable selection in a psycholexical investigation can substantively change the structure recovered even when holding analytic methodology constant (Saucier, 1997). As an obvious example, consider the low-moderate agreement of this data with the Big Five, despite applying the same methodology used to recover the Big Five and the dataset being from the Eugene-Springfield Community Sample.

Second, this is a non-diverse sample, which makes generalizing even valid sample-derived insights inappropriate. This dataset was drawn from the Eugene-Springfield Community Sample. This population has had an outsized impact on the theory of personality structure, in part because the associated university had historically been a nexus of personality research.

Last, and befitting such a work, there are innumerable individual differences and term characteristics that may impact responses to terms. Study 3 demonstrated that some methods are robust to some, but not all, of them. A theory rigorously linking personality factors, individual differences, and methods factors to ratings is necessary to simulate data with the verisimilitude requisite to determine the optimal analytic approach. This has been a historically neglected area of lexical research.

A fundamental decision in developing a personality structure appears to be whether or not to employ the lexical postulate. This determination depends largely on whether one believes that it provides a comprehensive and (ideally) relatively unbiased sample of personality trait descriptors. In the affirmative case, network models would be a prudent analytic approach. A researcher could then focus their efforts on identifying the trait descriptors to query, as well as the populations they aim to describe. However, there is scant little research directly assessing the validity of the lexical postulate (Uher, 2013; D. Wood, 2015). Its intuitive appeal—and absence of a similarly compelling approach—has allowed it to thrive without even a consensus as to an exact specification that would permit testing. This curious given the methodological consistency in lexical implementations, which, analytic advances notwithstanding, have been consistent since the time of Thurstone (1934). Effectively, the methods preceded the theory.

If one is inclined to eschew the lexical postulate but still aims to develop a population-level trait taxonomy from self-reported items, the same analytic approach could still be employed. However, the choice of variables to include would expand dramatically. The International Personality Item Pool would provide a valuable resource for extant items. Yet, again, defending the items ultimately included would be a crucial step, ideally incorporating research on the scope of personality, which could no longer be assumed to be well-covered in those variables. This approach would constitute the simplest pivot from a lexical investigation. However, there are many conceivable alternative approaches that would need different methods. These include inferences from online activity, smartphone/wearable device data, lexical analyses from other text sources, and more. Given the vast scope of personality, no single approach may provide a complete answer, but some sources of data may better lend themselves to describing particular domains of personality.

Given the concerns described early on in this work, the lexical postulate seems to constrain more than focus. It directs attention to a set of descriptors (adjectives) based on assumptions that don't seem well-supported. Its primary (dubious) benefit is that provides a comprehensive set of descriptors. Yet, researchers could surely include those descriptors in their set, if desired. The lexical postulate appeals to researchers because it is parsimonious, defensible, persuasive, and by now, tradition. Those scientific comforts may be keeping us from something better.

Chapter 5: Conclusion

The primary goal of this dissertation was to compare dimension reduction approaches for a psycholexical investigation. The findings instead suggest a need for deeper understanding of the psychometrics underlying lexical data. None of the algorithms used could be implemented without caveat. However, it is revealing that the algorithms eventually implemented were selected from the network psychometrics approach. The suite of tools available in the *EGAnet* package makes it appealing means of implementing a network psychometric approach, although it was too slow for this simulation study. The *EGAnet* package implements EBICGLASSO regularization; while community detection algorithms on the adaptive lasso-regularized network and the fully-connected zero order network were effective, these cannot be unequivocally recommended. Using the zero-order network undermines the foundation of network psychometrics, which is to treat partial correlations as causal links among variables. The case against the adaptive lasso is more tenuous. Epskamp and Fried (2018) note that the adaptive lasso should not be used with ordinal data. Treating items with eight response options (as in this study) as continuous is generally agreed to be defensible, and issues associated with treating most ordinal data as continuous may be overstated anyway (Robitzsch, 2020). However, the comparable performance of the adaptive lasso to the EBICGLASSO does not suggest revising the *EGAnet* approach.

In sum, there appears to be evidence for a "Big Few" model of personality, though it may generalize poorly as the assessed population diverges from WEIRD-ness. This is concerning for any theorist claiming universal personality structure but less so for those aiming to employ a wide-bandwidth scale in WEIRD populations. While this work directly speaks to structures such as the Big Five or HEXACO, the implications for integrative personality theories such as Whole Trait theory (Fleeson & Jayawickreme, 2015) or Cybernetic Big Five (Fleeson & Jayawickreme, 2015) are more equivocal. Whole Trait theory linked social-cognitive factors to the Big Five, which is not contradicted by this work. Instead, it would be of interest to compare the predictive validity of those social-cognitive factors against this newer structure, or indeed others such from Saucier & Iurino (2020). Cybernetic Big Five theory is more substantively linked to the Big Five, with one critical claim genetically linking two aspects for each of the five factors; these aspects may have some correlate within some substructure of this work that was not explored. Regardless, those studies having used the Big Five as a basis to search for a causal mechanism highlights the importance of using statistical validity even though statistical validity is not sufficient to imply causality.

The most critical finding from Study 1 is that a mismatch between study design and analytic approach can severely impair the ability of even the best dimension detection algorithms. Unidimensionality, low factor loadings, high factor intercorrelations, and low sample sizes were all implicated. Study 2 added the consideration for data processing (ipsatization) and theory (bifactor structure). Study 3 reaffirmed these past findings and added additional nuance that even equivalently performing approaches can still yield appreciably different approaches. These findings can be exported to other areas of personality research, and beyond. For instance, a study of the structure of narrative identity (McLean et al., 2020) could be re-analyzed under a similar paradigm with expert opinion caveating generative model concerns. Related work on the structure of goals, values, and motivation could also be done, though again, expert opinion should guide the process. In sum, these studies demonstrate two problems common to psychological research: the right statistical model is not always obvious, and statistics alone cannot always decide between competing models.

The findings of this work should be not interpreted as the new structure of personality. In fact, the sensitivity of analytic method provides good reason against such an interpretation. A strength of this work is that it makes the limitations of that analysis explicit, even as those limitations pervade works in the lexical tradition.

The first choice in developing a personality model is to decide why: how will such a model be used? A wide-bandwidth model such as the one described in this work makes no claims at being causal and will likely be only slightly predictive of a wide range of situations. Furthermore, a rigorous structure of personality is not needed for effective prediction. In many cases, a more granular model would be more prudent (Mõttus et al., 2017b; Paunonen & Ashton, 2001), and there may be an extant dataset sufficiently linking personality to the outcome of interest to serve as a basis for a narrower scope of personality (e.g., Brim et al., 2004; Goebel et al., 2019; Juster & Suzman, 1995; Watson & Wooden, 2021).

As demonstrated, researchers make such innumerable decisions when assessing structure that an indisputable structure appears unlikely. An accurate trait model of personality may lead to a causal model of personality. However, the psycholexical approach surely constrains the possible dimensions of personality (albeit at the benefit of providing a testable framework) and may also bias the scope away from critical domains of personality. Therefore, academic debate around the subject may be the primary reason for study.

The limitations of trait-descriptive adjectives

There are numerous issues in developing a structure of personality. The first is also the most foundational: using trait-descriptive adjectives as the basis for a structure of personality, while convenient, carries numerous limitations.

Using natural language to taxonomize personality is inherently problematic due to the non-scientific use of language. Numerous steps have been taken to ameliorate this issue which is impossible to entirely resolve but may be minimized. The most basic step to ensure that terms are rated based on a consensus around its meaning has been to query raters as to their self-reported knowledge of the term (Goldberg, 1990; Norman, 1967; Saucier & Goldberg, 1996). However, these steps do not preclude a respondent from having a strong conviction about an idiosyncratic (i.e., wrong) definition of a term. The standard of psycholexical investigations can be raised by actually testing respondents on their knowledge of terms, as in Condon et al. (2022), or using such an assessment to develop the list of terms being assessed.

However, there would room for contextual error still. Consider the term *erratic*, which loads onto both Consientiousness and Neuroticism in the Big Five framework (Goldberg, 1990). When understood as inconsistent in planning, work ethic, or quality of work, *erratic* has clear implications for Conscientiousness. When understood as unpredictable in mood or response to stressors, *erratic* could well be conceptualized as a component of Neuroticism. Both are valid interpretations that cannot be differentiated when presented as a single term. To address this, a longer phrase giving adequate context would need to be employed. This logic informed development of the International Personality Item Pool (IPIP; Goldberg et al., 2006). Phrasing may present its own issues. Aggregating pre-established scales may induce a method factor from the scale in which some variance is attributed to the non-personological wording within each scale. The desire to employ phrases which function differently from single terms—even if more accurately—also means that past inferences on works employing single terms may not be germane.

A core proposition of the lexical postulate is that personality traits that are relevant to others and should be communicated are encoded into language. The resulting structure—personality as is relevant to others—may not be the optimal approach for a causal model. This foundational issue may explain some Big Two structures, by grouping personality terms describing the person as a social agent and the person as an autonomous agent. However, there are various other conjectures for the etiology of Big Two structures that do not claim it as an artifact of language (Block, 2010). Regardless, limitations of the lexical postulate are myriad. Moreover, the utility of the lexical postulate seems to overshadow its validity. It provides an implementation of a comprehensive structure of personality, which has been exceptionally fruitful to personality theorists. It has been so useful, in fact, that in the absence of an equally convenient competitive theory, there has been little discussion of whether its premises are well-founded; unfortunately, these premises appear increasingly untrue.

Meanwhile, research in personality beyond the lexical postulate has continued unabated but lacking a unifying theory. Thus, in the domain of personality structure, there seems to be a trade-off in whether to pursue theoretically defensible or empirically defensible research.

Considering the quality of data

In nonetheless pursuing the psycholexical postulate, the main issue is not so much algorithmic but a data quality issue. This is a sizable issue needing serious analysis. A large, diverse, sample rating a comprehensive set of terms is necessary at a minimum. A still more rigorous work would assess the frequency of term use and knowledge (though these should be strongly related) of terms. As well, the social desirability loading of terms should also be queried. These same considerations would hold when using phrased items.

There are various demographic considerations to be made. An obvious example is gender effects, but there are more nuanced issues, including race/ethnicity, urban/rural, nationality, and language. Cross-cultural consensus using an emic approach seems the gold standard for resolving group-based noninvariance. Although the emic approach (developing an indigenous structure) is appealing and may be optimal, it is clearly more resource intensive than the etic approach (exporting a structure to another culture). A middle ground would be an *etic* approach with an eye towards measurement invariance. However, it is difficult to ignore the effect of term selection on the recovered structure, and so an important caveat is that when developing a scale in a non-English language, the *emic* approach would provide a stronger foundation from which to assess the impact of less obvious threats to the psycholexical postulate.

Collecting such vast data is a daunting endeavor. The breadth of expertise and cost associated is probably infeasible for a single researcher to manage. The historic approach of querying convenience samples will not suffice. However, technological advances have brought exciting avenues for personality research. The internet allows more facile collaboration among researchers. Even more excitingly, internet users have responded in droves to online personality assessments such as the IPIP (Goldberg et al., 2006) and SAPA (Condon, 2018) projects. The use of smartphones or wearable technology is also promising, not only for survey-based methods (Wilson et al., 2017), but passive data collection too (De Montjoye et al., 2013). Last, the advent of Large Language Models to the field of natural language processing has the potential to aid in scale development (Fyffe et al., 2024), mine text for personological insight (Saeteros et al., 2025), and even serve as the basis for a lexical investigation (Cutler & Condon, 2022).

Again, the structure of personality will not be adjudicated through identifying the best algorithmic approach to extant data. The psycholexical postulate and analyses thereof reflect a moment in time for personality psychology. Neither is evergreen; the limitations of these and past analyses have been explicated. The lexical postulate provides a means of understanding the characteristics of people without having to directly measure those characteristics. In the face of limitations to trying to capture such a vast domain as human personality, researchers will need to be creative and extend beyond the normal approach. The amount of data needed for such an effort is staggering, but equally there are now resources for collecting and analyzing those data. Methods for analyzing those data are a small part of that consideration but are similarly improving.

The best analysis most effectively separates the signal from the noise. However, datasets in psycholexical research have numerous signals, not all of which are of equal interest. This is not an algorithmic problem to be solved, but a theoretic one. Regardless, the analytic approach should be validated in light of that theory.

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Appendices

Appendix A: Information Criteria Pilot Study Results

Table 27. Results of Information Criteria from Pilot Study

IC	Penalty	Accuracy	MAE	MBE	ARI
aic	adapt	0.77 [0.77, 0.77]	0.27 [0.27, 0.28]	-0.01 [-0.02, -0.01]	0.78 [0.78, 0.78]
aic	atan	0.74 [0.74, 0.74]	0.3 [0.3, 0.31]	0.00 [-0.01, 0.00]	0.75 [0.75, 0.75]
aic	exp	0.72 [0.72, 0.72]	0.33 [0.33, 0.33]	-0.03 [-0.03, -0.03]	0.73 [0.73, 0.73]
aic	lasso	0.74 [0.74, 0.74]	0.32 [0.32, 0.33]	-0.1 [-0.1, -0.1]	0.75 [0.75, 0.75]
aic	log	0.76 [0.76, 0.76]	0.29 [0.28, 0.29]	-0.01 [-0.01, -0.01]	0.77 [0.76, 0.77]
aic	mcp	0.72 [0.72, 0.73]	0.35 [0.34, 0.35]	-0.07 [-0.08, -0.07]	0.73 [0.73, 0.73]
aic	scad	0.73 [0.72, 0.73]	0.35 [0.34, 0.35]	-0.08 [-0.09, -0.08]	0.73 [0.73, 0.73]
aic	selo	0.74 [0.74, 0.74]	0.31 [0.3, 0.31]	-0.01 [-0.01, 0]	0.75 [0.75, 0.75]
aic	sica	0.75 [0.74, 0.75]	0.30 [0.30, 0.30]	0.00 [0.00, 0.00]	0.75 [0.75, 0.75]
bic	adapt	0.79 [0.79, 0.79]	0.25 [0.25, 0.26]	0.06 [0.06, 0.06]	0.80 [0.80, 0.80]
bic	atan	0.76 [0.76, 0.77]	0.28 [0.28, 0.28]	0.12 [0.12, 0.12]	0.77 [0.77, 0.77]
bic	exp	0.75 [0.74, 0.75]	0.29 [0.29, 0.3]	0.06 [0.06, 0.06]	0.76 [0.76, 0.76]
bic	lasso	0.79 [0.79, 0.79]	0.25 [0.25, 0.25]	0.00 [0.00, 0.01]	0.80 [0.80, 0.80]
bic	log	0.78 [0.78, 0.78]	0.26 [0.26, 0.27]	0.09 [0.08, 0.09]	0.79 [0.79, 0.79]
bic	mcp	0.77 [0.77, 0.78]	0.28 [0.28, 0.29]	0.05 [0.05, 0.05]	0.78 [0.78, 0.78]
bic	scad	0.77 [0.77, 0.77]	0.33 [0.32, 0.33]	-0.04 [-0.04, -0.04]	0.78 [0.78, 0.78]
bic	selo	0.76 [0.76, 0.77]	0.28 [0.28, 0.28]	0.12 [0.12, 0.12]	0.77 [0.77, 0.78]
bic	sica	0.77 [0.76, 0.77]	0.28 [0.28, 0.28]	0.12 [0.12, 0.12]	0.77 [0.77, 0.78]
ebic	adapt	0.75 [0.74, 0.75]	0.44 [0.44, 0.44]	-0.15 [-0.16, -0.15]	0.76 [0.76, 0.76]
ebic	atan	0.74 [0.74, 0.74]	0.34 [0.34, 0.34]	0.20 [0.19, 0.20]	0.76 [0.76, 0.76]
ebic	exp	0.75 [0.74, 0.75]	0.3 [0.3, 0.3]	0.08 [0.08, 0.09]	0.76 [0.76, 0.76]
ebic	lasso	0.76 [0.76, 0.76]	0.37 [0.37, 0.38]	-0.13 [-0.14, -0.13]	0.76 [0.76, 0.76]
ebic	log	0.74 [0.74, 0.74]	0.45 [0.45, 0.46]	-0.1 [-0.11, -0.1]	0.76 [0.75, 0.76]
ebic	mcp	0.75 [0.75, 0.75]	0.35 [0.35, 0.36]	0.00 [-0.01, 0.00]	0.74 [0.74, 0.75]
ebic	scad	0.69 [0.69, 0.70]	0.67 [0.67, 0.68]	-0.45 [-0.46, -0.44]	0.71 [0.71, 0.71]
ebic	selo	0.74 [0.74, 0.75]	0.34 [0.33, 0.34]	0.20 [0.19, 0.20]	0.76 [0.76, 0.77]
ebic	sica	0.74 [0.74, 0.74]	0.35 [0.34, 0.35]	0.17 [0.17, 0.18]	0.76 [0.76, 0.76]
gic_1	adapt	0.79 [0.79, 0.79]	0.25 [0.25, 0.26]	0.06 [0.06, 0.06]	0.80 [0.80, 0.80]
gic_1	atan	0.76 [0.76, 0.76]	0.28 [0.28, 0.28]	0.12 [0.12, 0.12]	0.77 [0.77, 0.77]
gic_1	exp	0.75 [0.74, 0.75]	0.29 [0.29, 0.3]	0.06 [0.05, 0.06]	0.76 [0.76, 0.76]
gic_1	lasso	0.79 [0.79, 0.79]	0.25 [0.25, 0.25]	0.00 [0.00, 0.01]	0.80 [0.80, 0.80]
gic_1	log	0.78 [0.78, 0.78]	0.26 [0.26, 0.27]	0.09 [0.08, 0.09]	0.79 [0.79, 0.79]
gic_1	mcp	0.77 [0.77, 0.78]	0.28 [0.28, 0.29]	0.05 [0.05, 0.05]	0.78 [0.78, 0.78]
gic_1	scad	0.77 [0.77, 0.77]	0.33 [0.32, 0.33]	-0.04 [-0.05, -0.04]	0.78 [0.78, 0.78]
gic_1	selo	0.77 [0.76, 0.77]	0.28 [0.28, 0.28]	0.12 [0.12, 0.12]	0.77 [0.77, 0.78]
gic_1	sica	0.77 [0.76, 0.77]	0.28 [0.28, 0.28]	0.12 [0.12, 0.12]	0.77 [0.77, 0.78]

gic_2	adapt	0.78 [0.78, 0.78]	0.26 [0.26, 0.26]	0.00 [0.00, 0.01]	0.79 [0.79, 0.79]
gic_2	atan	0.76 [0.75, 0.76]	0.28 [0.28, 0.29]	0.02 [0.02, 0.03]	0.76 [0.76, 0.76]
gic_2	exp	0.73 [0.73, 0.73]	0.32 [0.32, 0.32]	-0.01 [-0.01, -0.01]	0.74 [0.74, 0.74]
gic_2	lasso	0.76 [0.76, 0.76]	0.30 [0.29, 0.30]	-0.07 [-0.08, -0.07]	0.77 [0.76, 0.77]
gic_2	log	0.77 [0.77, 0.77]	0.27 [0.27, 0.27]	0.01 [0.01, 0.02]	0.78 [0.78, 0.78]
gic_2	mcp	0.75 [0.75, 0.75]	0.31 [0.31, 0.32]	-0.03 [-0.04, -0.03]	0.75 [0.75, 0.76]
gic_2	scad	0.75 [0.75, 0.75]	0.31 [0.31, 0.31]	-0.05 [-0.05, -0.04]	0.75 [0.75, 0.76]
gic_2	selo	0.76 [0.75, 0.76]	0.29 [0.28, 0.29]	0.02 [0.02, 0.02]	0.76 [0.76, 0.76]
gic_2	sica	0.76 [0.76, 0.76]	0.28 [0.28, 0.29]	0.02 [0.02, 0.03]	0.76 [0.76, 0.77]
gic_3	adapt	0.79 [0.79, 0.80]	0.26 [0.25, 0.26]	0.05 [0.05, 0.06]	0.81 [0.8, 0.81]
gic_3	atan	0.77 [0.77, 0.77]	0.27 [0.27, 0.28]	0.13 [0.12, 0.13]	0.78 [0.78, 0.79]
gic_3	exp	0.75 [0.75, 0.75]	0.29 [0.29, 0.29]	0.06 [0.06, 0.06]	0.76 [0.76, 0.76]
gic_3	lasso	0.79 [0.79, 0.79]	0.25 [0.25, 0.26]	0.01 [0.01, 0.01]	0.80 [0.80, 0.80]
gic_3	log	0.79 [0.79, 0.79]	0.26 [0.26, 0.27]	0.08 [0.08, 0.09]	0.80 [0.80, 0.80]
gic_3	mcp	0.78 [0.78, 0.78]	0.28 [0.28, 0.28]	0.05 [0.04, 0.05]	0.79 [0.79, 0.79]
gic_3	scad	0.77 [0.77, 0.78]	0.33 [0.33, 0.34]	-0.05 [-0.05, -0.04]	0.78 [0.78, 0.79]
gic_3	selo	0.77 [0.77, 0.78]	0.27 [0.27, 0.28]	0.13 [0.12, 0.13]	0.79 [0.78, 0.79]
gic_3	sica	0.77 [0.77, 0.78]	0.27 [0.27, 0.28]	0.13 [0.12, 0.13]	0.79 [0.78, 0.79]
gic_4	adapt	0.79 [0.79, 0.79]	0.30 [0.30, 0.30]	0.00 [0.00, 0.01]	0.80 [0.80, 0.80]
gic_4	atan	0.77 [0.77, 0.77]	0.29 [0.29, 0.29]	0.17 [0.17, 0.17]	0.79 [0.79, 0.79]
gic_4	exp	0.75 [0.75, 0.75]	0.29 [0.29, 0.30]	0.08 [0.07, 0.08]	0.76 [0.76, 0.77]
gic_4	lasso	0.79 [0.79, 0.80]	0.27 [0.27, 0.27]	-0.01 [-0.01, 0]	0.80 [0.80, 0.80]
gic_4	log	0.78 [0.78, 0.78]	0.31 [0.31, 0.32]	0.04 [0.03, 0.04]	0.79 [0.79, 0.8]
gic_4	mcp	0.78 [0.78, 0.78]	0.29 [0.29, 0.30]	0.04 [0.03, 0.04]	0.78 [0.78, 0.79]
gic_4	scad	0.76 [0.76, 0.76]	0.42 [0.42, 0.43]	-0.16 [-0.16, -0.15]	0.77 [0.77, 0.77]
gic_4	selo	0.77 [0.77, 0.77]	0.29 [0.28, 0.29]	0.17 [0.17, 0.17]	0.79 [0.79, 0.79]
gic_4	sica	0.77 [0.77, 0.77]	0.29 [0.29, 0.29]	0.16 [0.16, 0.16]	0.79 [0.78, 0.79]
gic_5	adapt	0.79 [0.79, 0.80]	0.25 [0.24, 0.25]	0.06 [0.06, 0.06]	0.81 [0.8, 0.81]
gic_5	atan	0.77 [0.77, 0.77]	0.27 [0.27, 0.27]	0.11 [0.1, 0.11]	0.78 [0.78, 0.78]
gic_5	exp	0.75 [0.75, 0.75]	0.29 [0.29, 0.30]	0.05 [0.05, 0.05]	0.76 [0.76, 0.76]
gic_5	lasso	0.79 [0.79, 0.79]	0.26 [0.25, 0.26]	0.00 [0.00, 0.01]	0.80 [0.80, 0.80]
gic_5	log	0.79 [0.79, 0.79]	0.25 [0.25, 0.26]	0.08 [0.08, 0.09]	0.80 [0.80, 0.80]
gic_5	mcp	0.78 [0.77, 0.78]	0.28 [0.27, 0.28]	0.04 [0.04, 0.05]	0.79 [0.78, 0.79]
gic_5	scad	0.77 [0.77, 0.78]	0.31 [0.30, 0.31]	-0.02 [-0.03, -0.02]	0.78 [0.78, 0.79]
gic_5	selo	0.77 [0.77, 0.78]	0.27 [0.27, 0.27]	0.11 [0.10, 0.11]	0.78 [0.78, 0.78]
gic_5	sica	0.77 [0.77, 0.78]	0.27 [0.27, 0.27]	0.11 [0.10, 0.11]	0.78 [0.78, 0.79]
gic_6	adapt	0.67 [0.67, 0.67]	0.73 [0.72, 0.73]	-0.49 [-0.5, -0.48]	0.68 [0.68, 0.68]
gic_6	atan	0.71 [0.71, 0.72]	0.40 [0.39, 0.40]	0.20 [0.19, 0.20]	0.74 [0.73, 0.74]
gic_6	exp	0.75 [0.74, 0.75]	0.30 [0.30, 0.30]	0.09 [0.08, 0.09]	0.76 [0.76, 0.76]
gic_6	lasso	0.68 [0.68, 0.68]	0.64 [0.63, 0.64]	-0.44 [-0.45, -0.44]	0.68 [0.68, 0.68]
gic_6	log	0.67 [0.67, 0.67]	0.72 [0.71, 0.72]	-0.41 [-0.42, -0.4]	0.68 [0.68, 0.69]
gic_6	mcp	0.70 [0.70, 0.70]	0.44 [0.44, 0.45]	-0.07 [-0.07, -0.07]	0.69 [0.68, 0.69]
gic_6	scad	0.61 [0.61, 0.61]	1.00 [0.99, 1.00]	-0.81 [-0.82, -0.8]	0.63 [0.62, 0.63]
gic_6	selo	0.72 [0.71, 0.72]	0.40 [0.39, 0.40]	0.20 [0.19, 0.20]	0.74 [0.74, 0.74]
gic_6	sica	0.71 [0.70, 0.71]	0.42 [0.42, 0.43]	0.15 [0.15, 0.16]	0.72 [0.72, 0.72]

Appendix B: Study 1 Heatmaps

Table 28. Accuracy Partial Eta Squared by Term Interaction (Part 1)

Term	walktrap_atan_bic	louvain_atan_bic	leiden_atan_bic	walktrap_atan_gic_3	louvain_atan_gic_3	leiden_atan_gic_3	walktrap_atan_gic_4	louvain_atan_gic_4	leiden_atan_gic_4	walktrap_atan_ebic	louvain_atan_ebic	leiden_atan_ebic
balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor	.11	.09	.08	.11	.08	.08	.12	.10	.09	.10	.07	.07
fct	.09	.04	.04	.09	.03	.04	.05	.03	.03	.03	.02	.02
items	.00	.00	.00	.00	.01	.00	.00	.01	.01	.01	.01	.01
linear	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
loading	.30	.27	.26	.31	.28	.27	.37	.34	.34	.44	.43	.43
responses	.12	.09	.09	.11	.08	.09	.06	.05	.05	.05	.03	.03
sample	.22	.22	.21	.21	.21	.22	.23	.22	.22	.22	.21	.21
balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:balance	.00	.01	.01	.00	.01	.01	.00	.01	.02	.01	.01	.02
fct:f_cor	.02	.01	.01	.03	.01	.01	.02	.01	.01	.02	.01	.01
fct:items	.02	.07	.06	.02	.06	.06	.03	.06	.06	.02	.05	.04
fct:linear	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:loading	.00	.00	.01	.01	.00	.00	.01	.00	.00	.01	.01	.00
fct:responses	.01	.01	.00	.01	.00	.00	.00	.01	.01	.00	.01	.01
fct:sample	.01	.01	.01	.00	.01	.01	.00	.01	.01	.00	.01	.01
items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
linear:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
linear:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
linear:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
linear:loading	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
loading:f_cor	.03	.02	.02	.03	.02	.02	.02	.02	.02	.02	.01	.01
loading:items	.00	.00	.00	.00	.00	.00	.01	.01	.01	.01	.01	.01
responses:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:f_cor	.00	.00	.00	.00	.00	.00	.01	.00	.00	.01	.00	.00
responses:items	.00	.01	.02	.00	.01	.01	.00	.01	.00	.00	.00	.00
responses:linear	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:loading	.01	.01	.01	.01	.01	.01	.00	.00	.00	.00	.00	.00
responses:sample	.03	.02	.02	.02	.02	.02	.01	.01	.01	.01	.01	.00
sample:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:f_cor	.00	.01	.00	.00	.01	.01	.00	.00	.00	.00	.00	.00
sample:items	.01	.02	.02	.02	.03	.03	.03	.04	.04	.02	.02	.03
sample:linear	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:loading	.03	.03	.03	.04	.04	.04	.07	.06	.06	.09	.09	.09
fct:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:items:f_cor	.01	.02	.02	.00	.02	.02	.01	.01	.02	.01	.01	.01

fct:linear:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:linear:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:linear:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:linear:loading	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:loading:balance	.00	.01	.00	.00	.01	.01	.00	.01	.01	.01	.01	.01
fct:loading:f_cor	.01	.00	.00	.01	.00	.00	.01	.00	.00	.00	.00	.00
fct:loading:items	.01	.02	.02	.01	.01	.01	.01	.01	.01	.00	.01	.01
fct:responses:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:items	.00	.00	.00	.00	.01	.01	.00	.01	.01	.00	.00	.00
fct:responses:linear	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:loading	.01	.02	.02	.01	.01	.01	.01	.01	.01	.00	.00	.01
fct:responses:sample	.00	.01	.01	.00	.01	.01	.00	.01	.00	.01	.01	.01
fct:sample:balance	.00	.00	.01	.00	.01	.01	.01	.01	.01	.00	.01	.01
fct:sample:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:sample:items	.01	.02	.01	.00	.01	.01	.00	.00	.01	.00	.00	.00
fct:sample:linear	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:sample:loading	.02	.02	.02	.02	.01	.02	.01	.01	.01	.01	.01	.01
items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
linear:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
linear:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
linear:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
linear:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
linear:loading:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
linear:loading:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
loading:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
loading:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:linear:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:linear:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:linear:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:linear:loading	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:loading:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:loading:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:f_cor	.01	.00	.01	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:items	.00	.01	.01	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:linear	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:loading	.05	.04	.04	.04	.03	.04	.03	.03	.03	.02	.01	.01
sample:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:linear:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:linear:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:linear:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:linear:loading	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:loading:f_cor	.02	.03	.03	.03	.04	.04	.05	.05	.04	.05	.04	.05
sample:loading:items	.01	.01	.01	.01	.02	.01	.02	.02	.02	.02	.02	.02
fct:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:linear:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:linear:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:linear:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:linear:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.01	.00

fct:linear:loading:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:linear:loading:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:loading:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:loading:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:linear:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:linear:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:linear:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:linear:loading	.01	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.01	.00	.00
fct:responses:loading:f_cor	.01	.00	.00	.01	.01	.01	.00	.00	.00	.00	.00	.00
fct:responses:loading:items	.01	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:sample:balance	.01	.00	.00	.01	.00	.00	.01	.01	.01	.00	.01	.01
fct:responses:sample:f_cor	.00	.00	.00	.00	.01	.01	.01	.00	.00	.01	.00	.00
fct:responses:sample:items	.01	.01	.01	.00	.01	.01	.01	.01	.01	.01	.01	.01
fct:responses:sample:linear	.00	.00	.00	.00	.01	.00	.00	.00	.01	.00	.00	.00
fct:responses:sample:loading	.01	.01	.01	.01	.02	.01	.00	.01	.01	.01	.01	.01
fct:sample:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:sample:items:balance	.00	.00	.00	.00	.01	.00	.00	.01	.01	.01	.01	.01
fct:sample:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.01	.00	.00	.00	.00
fct:sample:linear:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:sample:linear:f_cor	.00	.00	.00	.00	.00	.00	.00	.01	.00	.00	.00	.00
fct:sample:linear:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:sample:linear:loading	.01	.01	.01	.01	.01	.01	.01	.00	.00	.00	.00	.01
fct:sample:loading:balance	.00	.01	.01	.00	.01	.01	.01	.01	.01	.00	.01	.01
fct:sample:loading:f_cor	.01	.01	.01	.01	.01	.01	.02	.01	.01	.01	.01	.01
fct:sample:loading:items	.00	.01	.01	.01	.01	.01	.00	.01	.02	.00	.02	.01
linear:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
linear:loading:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
linear:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
linear:loading:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
loading:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:linear:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:linear:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:linear:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:linear:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:linear:loading:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:linear:loading:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:loading:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:loading:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:linear:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:linear:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:linear:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:linear:loading	.00	.00	.00	.00	.00	.00	.00	.00	.00	.01	.00	.00
responses:sample:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.01	.00	.00	.00
responses:sample:loading:f_cor	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01
responses:sample:loading:items	.00	.01	.01	.00	.00	.01	.00	.00	.00	.01	.01	.01
sample:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:linear:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:linear:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00

sample:linear:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:linear:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:linear:loading:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:linear:loading:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:loading:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.01	.00
sample:loading:items:balance	.00	.00	.00	.00	.00	.00	.01	.00	.00	.00	.00	.00
sample:loading:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.01	.00	.00	.00	.00
fct:linear:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:linear:loading:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:linear:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:linear:loading:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:loading:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.01	.01
fct:responses:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:linear:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:linear:items:balance	.00	.00	.00	.01	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:linear:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:linear:loading:balance	.00	.00	.01	.00	.01	.00	.00	.00	.00	.00	.00	.00
fct:responses:linear:loading:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.01
fct:responses:linear:loading:items	.00	.00	.00	.00	.00	.00	.01	.00	.01	.00	.00	.00
fct:responses:loading:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.01	.00	.00
fct:responses:loading:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.01	.01	.00	.00	.00
fct:responses:sample:balance:f_cor	.00	.00	.00	.00	.00	.00	.01	.00	.00	.00	.00	.00
fct:responses:sample:items:balance	.00	.00	.01	.00	.00	.00	.01	.00	.01	.01	.00	.01
fct:responses:sample:items:f_cor	.00	.00	.00	.00	.00	.01	.00	.00	.01	.00	.00	.00
fct:responses:sample:linear:balance	.00	.01	.01	.00	.01	.01	.00	.01	.01	.00	.00	.01
fct:responses:sample:linear:f_cor	.00	.00	.01	.00	.01	.01	.00	.01	.01	.00	.00	.00
fct:responses:sample:linear:items	.00	.00	.00	.00	.00	.00	.01	.00	.00	.00	.01	.00
fct:responses:sample:linear:loading	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01
fct:responses:sample:loading:balance	.01	.01	.01	.01	.01	.01	.01	.01	.02	.01	.01	.01
fct:responses:sample:loading:f_cor	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01
fct:responses:sample:loading:items	.01	.01	.01	.01	.01	.01	.01	.01	.02	.01	.01	.01
fct:sample:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.01	.01	.00	.00	.00
fct:sample:linear:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.01	.00
fct:sample:linear:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:sample:linear:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:sample:linear:loading:balance	.00	.01	.00	.00	.01	.01	.01	.00	.01	.01	.00	.00
fct:sample:linear:loading:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.01	.00	.00
fct:sample:linear:loading:items	.00	.00	.00	.01	.00	.00	.00	.00	.00	.00	.00	.00
fct:sample:loading:balance:f_cor	.00	.01	.01	.00	.00	.01	.00	.00	.00	.00	.00	.00
fct:sample:loading:items:balance	.00	.00	.00	.00	.01	.00	.01	.01	.01	.00	.01	.01
fct:sample:loading:items:f_cor	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01
linear:loading:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:linear:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:linear:loading:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:linear:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:linear:loading:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:loading:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:linear:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:linear:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:linear:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:linear:loading:balance	.00	.00	.01	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:linear:loading:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:linear:loading:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:loading:balance:f_cor	.00	.01	.00	.00	.01	.00	.01	.00	.00	.00	.00	.00
responses:sample:loading:items:balance	.01	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:loading:items:f_cor	.00	.00	.00	.00	.01	.00	.00	.00	.00	.01	.00	.00

sample:linear:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:linear:loading:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:linear:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:linear:loading:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:loading:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:linear:loading:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:linear:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:linear:loading:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:linear:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:linear:loading:items:f_cor	.00	.00	.00	.01	.00	.00	.00	.00	.01	.00	.00	.00
fct:responses:loading:items:balance:f_cor	.01	.00	.00	.01	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:sample:items:balance:f_cor	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01
fct:responses:sample:linear:balance:f_cor	.01	.00	.01	.01	.01	.01	.01	.00	.00	.01	.00	.00
fct:responses:sample:linear:items:balance	.01	.01	.01	.00	.01	.01	.00	.00	.00	.00	.00	.00
fct:responses:sample:linear:items:f_cor	.01	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:sample:linear:loading:balance	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01	.02
fct:responses:sample:linear:loading:f_cor	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01
fct:responses:sample:linear:loading:items	.01	.01	.01	.00	.01	.01	.01	.01	.01	.01	.01	.01
fct:responses:sample:loading:balance:f_cor	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01
fct:responses:sample:loading:items:balance	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01
fct:responses:sample:loading:items:f_cor	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01
fct:sample:linear:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.01	.00	.00	.00	.00	.00
fct:sample:linear:loading:balance:f_cor	.01	.01	.01	.01	.01	.01	.01	.00	.00	.00	.00	.01
fct:sample:linear:loading:items:balance	.01	.00	.01	.00	.00	.00	.00	.00	.01	.00	.00	.00
fct:sample:linear:loading:items:f_cor	.00	.00	.00	.01	.00	.00	.00	.01	.01	.01	.01	.01
fct:sample:loading:items:balance:f_cor	.01	.01	.01	.01	.00	.01	.01	.01	.01	.01	.01	.01
responses:linear:loading:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:linear:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:linear:loading:balance:f_cor	.00	.01	.00	.01	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:linear:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.01	.01	.00	.00	.00
responses:sample:linear:loading:items:f_cor	.00	.00	.01	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:loading:items:balance:f_cor	.01	.00	.00	.01	.00	.00	.00	.00	.00	.00	.00	.00
sample:linear:loading:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:linear:loading:items:balance:f_cor	.01	.01	.01	.00	.00	.01	.00	.00	.00	.00	.00	.00
fct:responses:sample:linear:items:balance:f_cor	.00	.00	.01	.00	.00	.01	.01	.00	.01	.01	.00	.01
fct:responses:sample:linear:loading:balance:f_cor	.01	.01	.01	.01	.01	.02	.01	.01	.01	.01	.01	.01
fct:responses:sample:linear:loading:items:balance	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01
fct:responses:sample:linear:loading:items:f_cor	.01	.01	.01	.01	.01	.01	.00	.01	.01	.01	.01	.01
fct:responses:sample:loading:items:balance:f_cor	.02	.01	.01	.02	.01	.01	.01	.01	.01	.01	.01	.01
fct:sample:linear:loading:items:balance:f_cor	.01	.00	.01	.01	.00	.01	.01	.00	.00	.01	.00	.00
responses:sample:linear:loading:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:sample:linear:loading:items:balance:f_cor	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01

Table 29. Accuracy Partial Eta Squared by Term Interaction (Part 2)

Term	walktrap_lasso_bic	louvain_lasso_bic	leiden_lasso_bic	walktrap_lasso_gic_3	louvain_lasso_gic_3	leiden_lasso_gic_3	walktrap_lasso_gic_4	louvain_lasso_gic_4	leiden_lasso_gic_4	walktrap_lasso_ebic	louvain_lasso_ebic	leiden_lasso_ebic
balance	.00	.00	.01	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor	.16	.09	.09	.16	.09	.09	.19	.11	.11	.16	.10	.11
fct	.20	.12	.12	.19	.12	.11	.17	.12	.13	.15	.12	.12
items	.02	.00	.01	.03	.01	.01	.02	.00	.00	.01	.00	.00
linear	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
loading	.23	.23	.23	.24	.25	.23	.34	.32	.32	.51	.50	.51
responses	.21	.16	.15	.19	.14	.13	.08	.06	.06	.01	.01	.01
sample	.19	.20	.20	.17	.19	.19	.20	.23	.23	.27	.29	.29
balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:balance	.00	.01	.01	.00	.00	.00	.00	.00	.01	.00	.00	.00
fct:f_cor	.05	.02	.02	.04	.02	.03	.06	.03	.03	.06	.04	.04
fct:items	.02	.07	.08	.03	.08	.09	.03	.06	.05	.02	.03	.03
fct:linear	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:loading	.02	.01	.01	.03	.01	.01	.05	.03	.03	.05	.04	.04
fct:responses	.04	.01	.01	.02	.01	.01	.00	.02	.02	.00	.01	.02
fct:sample	.01	.01	.01	.01	.01	.01	.01	.01	.01	.00	.00	.01
items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
items:f_cor	.02	.00	.01	.01	.00	.01	.02	.00	.01	.02	.01	.01
linear:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
linear:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
linear:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
linear:loading	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
loading:f_cor	.04	.03	.03	.04	.03	.03	.05	.03	.03	.04	.02	.03
loading:items	.01	.01	.01	.01	.01	.01	.01	.00	.00	.01	.01	.01
responses:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:items	.01	.02	.02	.00	.01	.01	.00	.00	.00	.00	.00	.00
responses:linear	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:loading	.02	.01	.01	.02	.01	.01	.01	.01	.01	.01	.01	.01
responses:sample	.06	.06	.06	.05	.04	.04	.02	.02	.02	.00	.00	.00
sample:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:f_cor	.01	.00	.01	.01	.00	.00	.00	.00	.00	.00	.00	.00
sample:items	.00	.01	.01	.00	.01	.01	.01	.01	.01	.00	.01	.01
sample:linear	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:loading	.01	.02	.03	.01	.03	.03	.03	.06	.06	.13	.16	.16
fct:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:items:balance	.00	.00	.00	.01	.00	.00	.00	.00	.00	.00	.00	.00
fct:items:f_cor	.01	.01	.02	.01	.01	.02	.01	.02	.01	.01	.01	.01
fct:linear:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:linear:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:linear:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:linear:loading	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00

fct:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.01	.00	.00	.00
fct:loading:f_cor	.01	.00	.00	.01	.01	.01	.02	.01	.01	.01	.01	.01
fct:loading:items	.01	.01	.02	.01	.01	.02	.00	.01	.00	.00	.00	.00
fct:responses:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:f_cor	.00	.00	.01	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:items	.00	.01	.01	.00	.02	.02	.01	.02	.01	.01	.01	.01
fct:responses:linear	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:loading	.02	.02	.03	.03	.03	.03	.01	.02	.02	.00	.00	.00
fct:responses:sample	.01	.01	.00	.01	.01	.00	.00	.01	.02	.01	.01	.01
fct:sample:balance	.00	.01	.01	.00	.00	.01	.00	.00	.00	.00	.00	.00
fct:sample:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:sample:items	.00	.01	.01	.00	.01	.01	.00	.00	.00	.00	.00	.00
fct:sample:linear	.00	.00	.00	.00	.00	.01	.00	.00	.00	.00	.00	.00
fct:sample:loading	.02	.02	.02	.01	.01	.01	.02	.02	.02	.04	.03	.03
items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
linear:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
linear:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
linear:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
linear:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
linear:loading:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
linear:loading:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
loading:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
loading:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:linear:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:linear:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:linear:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:linear:loading	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:loading:f_cor	.00	.00	.00	.01	.00	.00	.01	.00	.00	.00	.00	.00
responses:loading:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.01	.00	.01
responses:sample:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:f_cor	.01	.00	.00	.01	.00	.00	.01	.00	.00	.00	.00	.00
responses:sample:items	.01	.02	.01	.00	.01	.01	.00	.00	.01	.00	.00	.00
responses:sample:linear	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:loading	.04	.04	.03	.04	.03	.04	.05	.04	.04	.02	.02	.02
sample:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:linear:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:linear:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:linear:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:linear:loading	.01	.00	.01	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:loading:f_cor	.04	.02	.02	.04	.02	.02	.04	.02	.02	.05	.04	.04
sample:loading:items	.01	.01	.02	.02	.02	.02	.02	.02	.01	.03	.03	.03
fct:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:linear:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:linear:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:linear:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:linear:loading:balance	.00	.00	.00	.00	.00	.00	.01	.01	.00	.00	.00	.00
fct:linear:loading:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:linear:loading:items	.00	.00	.00	.01	.00	.00	.01	.00	.00	.00	.00	.00
fct:loading:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00

fct:loading:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.01	.01	.00
fct:responses:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:items:balance	.00	.00	.00	.00	.00	.01	.00	.01	.00	.00	.00	.00
fct:responses:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:linear:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:linear:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.01	.00	.00	.00
fct:responses:linear:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:linear:loading	.00	.01	.01	.00	.00	.00	.00	.00	.00	.01	.00	.00
fct:responses:loading:balance	.00	.00	.00	.00	.00	.00	.00	.01	.00	.00	.00	.00
fct:responses:loading:f_cor	.01	.00	.00	.01	.00	.00	.00	.00	.00	.00	.01	.00
fct:responses:loading:items	.00	.00	.00	.00	.00	.00	.01	.00	.00	.00	.00	.00
fct:responses:sample:balance	.00	.01	.01	.01	.00	.00	.00	.01	.01	.00	.01	.00
fct:responses:sample:f_cor	.00	.00	.01	.00	.01	.00	.00	.00	.00	.01	.01	.01
fct:responses:sample:items	.00	.00	.00	.00	.00	.00	.00	.00	.01	.00	.00	.00
fct:responses:sample:linear	.00	.00	.01	.00	.00	.00	.00	.00	.01	.00	.00	.00
fct:responses:sample:loading	.02	.01	.02	.01	.02	.01	.02	.02	.01	.02	.02	.02
fct:sample:balance:f_cor	.00	.00	.01	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:sample:items:balance	.00	.00	.00	.00	.00	.00	.00	.01	.01	.00	.00	.00
fct:sample:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:sample:linear:balance	.00	.00	.00	.00	.00	.00	.00	.00	.01	.00	.00	.00
fct:sample:linear:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:sample:linear:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:sample:linear:loading	.00	.01	.01	.00	.01	.01	.00	.01	.01	.00	.01	.00
fct:sample:loading:balance	.00	.00	.01	.00	.01	.01	.01	.01	.01	.01	.01	.00
fct:sample:loading:f_cor	.01	.01	.01	.01	.01	.01	.01	.01	.01	.02	.01	.01
fct:sample:loading:items	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01
linear:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
linear:loading:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
linear:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
linear:loading:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
loading:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:linear:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:linear:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:linear:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:linear:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:linear:loading:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:linear:loading:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:loading:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:loading:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:linear:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:linear:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:linear:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:linear:loading	.00	.00	.00	.00	.00	.00	.00	.00	.00	.01	.00	.00
responses:sample:loading:balance	.01	.00	.00	.00	.00	.00	.01	.01	.01	.00	.00	.00
responses:sample:loading:f_cor	.01	.00	.00	.01	.00	.00	.00	.01	.01	.01	.00	.00
responses:sample:loading:items	.01	.01	.00	.00	.00	.01	.01	.00	.00	.01	.01	.01
sample:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:linear:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:linear:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:linear:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:linear:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:linear:loading:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:linear:loading:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00

sample:loading:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:loading:items:f_cor	.00	.00	.00	.01	.00	.00	.01	.01	.01	.00	.00	.00
fct:linear:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:linear:loading:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:linear:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:linear:loading:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:loading:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:linear:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:linear:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:linear:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:linear:loading:balance	.00	.01	.00	.00	.01	.00	.00	.00	.00	.00	.01	.00
fct:responses:linear:loading:f_cor	.00	.00	.01	.00	.00	.00	.01	.00	.01	.00	.00	.01
fct:responses:linear:loading:items	.00	.00	.00	.00	.01	.01	.00	.01	.01	.00	.00	.00
fct:responses:loading:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.01
fct:responses:loading:items:balance	.00	.01	.01	.01	.01	.01	.01	.00	.01	.00	.01	.01
fct:responses:loading:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.01
fct:responses:sample:balance:f_cor	.00	.00	.00	.01	.00	.00	.01	.00	.00	.01	.01	.01
fct:responses:sample:items:balance	.00	.01	.00	.00	.00	.00	.00	.01	.01	.01	.01	.01
fct:responses:sample:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:sample:linear:balance	.00	.01	.01	.00	.01	.01	.01	.01	.01	.00	.01	.01
fct:responses:sample:linear:f_cor	.00	.00	.00	.01	.01	.01	.01	.01	.00	.01	.01	.01
fct:responses:sample:linear:items	.00	.00	.01	.00	.00	.00	.01	.01	.01	.01	.00	.00
fct:responses:sample:linear:loading	.01	.02	.02	.01	.02	.02	.01	.01	.01	.01	.01	.01
fct:responses:sample:loading:balance	.01	.01	.01	.01	.01	.01	.01	.02	.01	.01	.01	.01
fct:responses:sample:loading:f_cor	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01	.02	.02
fct:responses:sample:loading:items	.01	.01	.01	.01	.01	.01	.01	.02	.02	.01	.01	.01
fct:sample:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.01	.00	.00	.00	.00
fct:sample:linear:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:sample:linear:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:sample:linear:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:sample:linear:loading:balance	.00	.00	.01	.00	.01	.01	.00	.01	.01	.00	.00	.00
fct:sample:linear:loading:f_cor	.00	.00	.01	.00	.01	.01	.00	.01	.01	.01	.01	.01
fct:sample:linear:loading:items	.00	.01	.01	.01	.01	.01	.01	.01	.01	.01	.00	.00
fct:sample:loading:balance:f_cor	.01	.01	.01	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:sample:loading:items:balance	.01	.00	.00	.01	.01	.01	.00	.00	.01	.00	.00	.00
fct:sample:loading:items:f_cor	.00	.01	.00	.00	.01	.01	.01	.01	.01	.01	.01	.01
linear:loading:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:linear:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:linear:loading:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:linear:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:linear:loading:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:loading:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:linear:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:linear:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:linear:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:linear:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.01
responses:sample:linear:loading:f_cor	.00	.00	.00	.00	.00	.00	.01	.00	.00	.00	.00	.00
responses:sample:linear:loading:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:loading:balance:f_cor	.00	.01	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.01	.00	.00	.00
responses:sample:loading:items:f_cor	.00	.00	.00	.00	.01	.01	.00	.01	.01	.00	.00	.01
sample:linear:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:linear:loading:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:linear:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:linear:loading:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00

sample:loading:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:linear:loading:items:balance:f_cor	.00	.00	.00	.00	.00	.01	.00	.00	.00	.00	.00	.00
fct:responses:linear:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:linear:loading:balance:f_cor	.00	.00	.00	.00	.00	.01	.00	.00	.00	.00	.00	.00
fct:responses:linear:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:linear:loading:items:f_cor	.00	.00	.00	.00	.00	.00	.01	.00	.00	.01	.00	.00
fct:responses:loading:items:balance:f_cor	.00	.01	.00	.00	.00	.01	.00	.00	.00	.00	.00	.01
fct:responses:sample:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.01	.01	.01	.00	.00	.00
fct:responses:sample:linear:balance:f_cor	.00	.01	.01	.00	.01	.00	.00	.01	.01	.01	.01	.01
fct:responses:sample:linear:items:balance	.00	.00	.00	.01	.00	.01	.01	.01	.00	.01	.00	.00
fct:responses:sample:linear:items:f_cor	.01	.00	.00	.01	.01	.01	.01	.00	.00	.01	.00	.00
fct:responses:sample:linear:loading:balance	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01
fct:responses:sample:linear:loading:f_cor	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01
fct:responses:sample:linear:loading:items	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01
fct:responses:sample:loading:balance:f_cor	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01
fct:responses:sample:loading:items:balance	.01	.01	.01	.01	.01	.02	.01	.01	.01	.01	.01	.02
fct:responses:sample:loading:items:f_cor	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01
fct:sample:linear:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:sample:linear:loading:balance:f_cor	.00	.01	.00	.01	.01	.00	.01	.01	.01	.01	.01	.01
fct:sample:linear:loading:items:balance	.00	.00	.00	.00	.00	.01	.01	.01	.01	.01	.01	.01
fct:sample:linear:loading:items:f_cor	.00	.01	.01	.00	.01	.01	.00	.01	.01	.00	.01	.01
fct:sample:loading:items:balance:f_cor	.00	.01	.01	.00	.01	.01	.00	.01	.01	.01	.01	.01
responses:linear:loading:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:linear:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:linear:loading:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.01	.01
responses:sample:linear:loading:items:balance	.00	.01	.01	.00	.01	.01	.00	.01	.01	.00	.00	.00
responses:sample:linear:loading:items:f_cor	.00	.00	.01	.00	.00	.00	.00	.01	.01	.00	.00	.00
responses:sample:loading:items:balance:f_cor	.00	.01	.00	.00	.00	.00	.00	.00	.00	.01	.00	.00
sample:linear:loading:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:linear:loading:items:balance:f_cor	.00	.00	.00	.00	.00	.01	.00	.00	.00	.00	.00	.00
fct:responses:sample:linear:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:sample:linear:loading:balance:f_cor	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01
fct:responses:sample:linear:loading:items:balance	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01
fct:responses:sample:linear:loading:items:f_cor	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01
fct:responses:sample:loading:items:balance:f_cor	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01
fct:sample:linear:loading:items:balance:f_cor	.01	.00	.00	.00	.01	.01	.00	.00	.00	.01	.00	.00
responses:sample:linear:loading:items:balance:f_cor	.00	.00	.01	.00	.01	.01	.00	.00	.00	.00	.00	.00
fct:responses:sample:linear:loading:items:balance:f_cor	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01

Table 30. Accuracy Partial Eta Squared by Term Interaction (Part 3)

Term	walktrap_adapt_bic	louvain_adapt_bic	leiden_adapt_bic	walktrap_adapt_gic_3	louvain_adapt_gic_3	leiden_adapt_gic_3	walktrap_adapt_gic_4	louvain_adapt_gic_4	leiden_adapt_gic_4	walktrap_adapt_ebic	louvain_adapt_ebic	leiden_adapt_ebic
balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor	.13	.09	.08	.13	.08	.08	.14	.09	.08	.11	.07	.08
fct	.13	.05	.06	.12	.06	.07	.11	.05	.06	.07	.04	.03
items	.01	.00	.00	.01	.00	.00	.01	.00	.00	.00	.00	.00
linear	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
loading	.30	.28	.29	.31	.30	.30	.42	.40	.40	.53	.54	.55
responses	.13	.09	.08	.11	.08	.07	.04	.04	.04	.01	.01	.01

sample	.20	.20	.21	.19	.20	.21	.22	.24	.24	.26	.28	.28
balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:balance	.00	.01	.01	.00	.01	.01	.00	.01	.01	.00	.00	.00
fct:f_cor	.05	.02	.02	.04	.01	.02	.04	.01	.01	.03	.01	.01
fct:items	.02	.07	.07	.03	.07	.07	.03	.06	.06	.01	.04	.04
fct:linear	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:loading	.01	.00	.00	.02	.01	.01	.03	.02	.02	.03	.02	.02
fct:responses	.02	.01	.01	.01	.01	.01	.00	.02	.01	.00	.01	.01
fct:sample	.00	.01	.01	.00	.01	.01	.00	.00	.01	.00	.01	.01
items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
items:f_cor	.01	.00	.00	.01	.00	.00	.01	.00	.00	.01	.00	.00
linear:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
linear:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
linear:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
linear:loading	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.01	.00
loading:f_cor	.03	.03	.02	.03	.02	.02	.03	.02	.02	.02	.02	.02
loading:items	.00	.00	.00	.01	.00	.00	.01	.01	.01	.01	.00	.00
responses:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.01	.00	.00
responses:items	.01	.01	.01	.00	.00	.00	.00	.01	.00	.00	.00	.00
responses:linear	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:loading	.01	.00	.00	.00	.00	.00	.00	.00	.00	.00	.01	.00
responses:sample	.05	.03	.03	.03	.02	.02	.01	.01	.01	.00	.00	.00
sample:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:f_cor	.01	.00	.00	.01	.00	.00	.00	.00	.00	.00	.00	.00
sample:items	.01	.01	.01	.01	.02	.02	.01	.01	.01	.00	.01	.01
sample:linear	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:loading	.03	.04	.05	.03	.06	.07	.10	.13	.14	.18	.20	.20
fct:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:items:f_cor	.01	.01	.01	.01	.01	.01	.01	.02	.02	.01	.01	.01
fct:linear:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:linear:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:linear:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:linear:loading	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:loading:balance	.01	.01	.01	.00	.01	.01	.00	.00	.00	.00	.00	.00
fct:loading:f_cor	.01	.00	.00	.01	.00	.00	.01	.00	.00	.01	.00	.00
fct:loading:items	.01	.02	.02	.01	.01	.01	.00	.01	.01	.00	.01	.01
fct:responses:balance	.00	.00	.00	.00	.01	.00	.00	.00	.00	.00	.00	.00
fct:responses:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:items	.00	.01	.01	.00	.01	.01	.00	.01	.01	.00	.01	.01
fct:responses:linear	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:loading	.02	.02	.02	.01	.01	.01	.01	.01	.01	.00	.00	.00
fct:responses:sample	.01	.01	.01	.00	.01	.01	.00	.02	.02	.01	.01	.01
fct:sample:balance	.00	.01	.01	.01	.01	.01	.00	.01	.01	.00	.00	.00
fct:sample:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:sample:items	.00	.01	.01	.00	.01	.01	.00	.01	.01	.00	.00	.00
fct:sample:linear	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:sample:loading	.03	.02	.02	.02	.01	.01	.01	.01	.01	.01	.01	.01
items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
linear:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
linear:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
linear:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
linear:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
linear:loading:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
linear:loading:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
loading:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00

loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
loading:items:f_cor	.00	.01	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:linear:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:linear:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:linear:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:linear:loading	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:loading:f_cor	.01	.00	.00	.01	.00	.00	.00	.00	.00	.00	.00	.00
responses:loading:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:items	.01	.01	.01	.01	.01	.01	.00	.00	.01	.00	.00	.00
responses:sample:linear	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:loading	.04	.04	.05	.05	.05	.05	.03	.04	.03	.01	.02	.02
sample:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:linear:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:linear:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:linear:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:linear:loading	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:loading:f_cor	.03	.02	.02	.03	.03	.03	.05	.03	.03	.04	.03	.04
sample:loading:items	.01	.00	.01	.02	.01	.01	.03	.02	.02	.01	.01	.01
fct:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:linear:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:linear:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:linear:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:linear:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.01
fct:linear:loading:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:linear:loading:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:loading:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:loading:items:f_cor	.01	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:linear:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:linear:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:linear:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:linear:loading	.01	.00	.00	.01	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:loading:balance	.00	.00	.00	.00	.01	.00	.00	.00	.00	.00	.00	.00
fct:responses:loading:f_cor	.01	.00	.01	.01	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:loading:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:sample:balance	.01	.01	.00	.01	.00	.01	.00	.01	.01	.00	.01	.01
fct:responses:sample:f_cor	.00	.01	.01	.01	.01	.00	.01	.00	.00	.01	.01	.01
fct:responses:sample:items	.01	.01	.01	.01	.01	.01	.00	.01	.01	.00	.01	.01
fct:responses:sample:linear	.00	.01	.00	.00	.00	.00	.00	.00	.00	.01	.01	.01
fct:responses:sample:loading	.02	.02	.02	.02	.02	.01	.01	.02	.02	.02	.02	.02
fct:sample:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:sample:items:balance	.00	.00	.00	.00	.00	.00	.00	.01	.01	.00	.00	.00
fct:sample:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:sample:linear:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:sample:linear:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:sample:linear:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00

fct:sample:linear:loading	.00	.00	.01	.00	.01	.01	.01	.01	.01	.01	.00	.00
fct:sample:loading:balance	.00	.01	.01	.00	.01	.01	.01	.01	.01	.00	.01	.00
fct:sample:loading:f_cor	.01	.00	.00	.01	.01	.01	.02	.01	.01	.01	.00	.00
fct:sample:loading:items	.01	.01	.01	.00	.01	.01	.00	.01	.01	.01	.01	.01
linear:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
linear:loading:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
linear:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
linear:loading:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
loading:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:linear:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:linear:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:linear:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:linear:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:linear:loading:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:linear:loading:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:loading:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:loading:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:linear:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:linear:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:linear:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:linear:loading	.00	.00	.00	.01	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:loading:balance	.01	.01	.01	.00	.01	.01	.00	.01	.01	.00	.00	.00
responses:sample:loading:f_cor	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01
responses:sample:loading:items	.00	.01	.01	.00	.00	.01	.00	.00	.00	.00	.00	.00
sample:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:linear:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:linear:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:linear:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:linear:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:linear:loading:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:linear:loading:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:loading:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:loading:items:f_cor	.00	.01	.01	.01	.01	.00	.01	.00	.00	.00	.00	.00
fct:linear:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.01	.00	.00	.00	.00	.00
fct:linear:loading:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:linear:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:linear:loading:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:loading:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.01	.00	.00	.00	.00
fct:responses:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:linear:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:linear:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:linear:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:linear:loading:balance	.00	.00	.01	.00	.01	.01	.00	.00	.00	.00	.00	.00
fct:responses:linear:loading:f_cor	.00	.00	.00	.00	.00	.00	.01	.00	.00	.00	.00	.00
fct:responses:linear:loading:items	.00	.00	.00	.00	.00	.00	.00	.01	.01	.00	.00	.00
fct:responses:loading:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:loading:items:balance	.01	.01	.00	.01	.01	.01	.00	.00	.00	.00	.00	.00
fct:responses:loading:items:f_cor	.00	.01	.01	.00	.00	.00	.01	.01	.01	.00	.00	.00
fct:responses:sample:balance:f_cor	.01	.00	.00	.01	.00	.00	.01	.00	.00	.00	.00	.00
fct:responses:sample:items:balance	.00	.00	.00	.00	.00	.00	.01	.01	.00	.01	.01	.01
fct:responses:sample:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.01	.00	.00	.00
fct:responses:sample:linear:balance	.00	.01	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00

fct:responses:sample:linear:f_cor	.00	.01	.00	.00	.01	.00	.00	.00	.00	.00	.01	.01
fct:responses:sample:linear:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.01	.00	.00
fct:responses:sample:linear:loading	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01
fct:responses:sample:loading:balance	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01
fct:responses:sample:loading:f_cor	.02	.02	.02	.01	.01	.01	.01	.01	.01	.01	.02	.02
fct:responses:sample:loading:items	.01	.01	.01	.01	.02	.02	.01	.01	.01	.01	.02	.01
fct:sample:items:balance:f_cor	.00	.01	.01	.00	.00	.00	.00	.01	.01	.00	.00	.00
fct:sample:linear:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:sample:linear:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:sample:linear:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:sample:linear:loading:balance	.00	.00	.00	.00	.00	.01	.00	.01	.00	.01	.00	.00
fct:sample:linear:loading:f_cor	.01	.00	.00	.01	.00	.01	.01	.01	.01	.01	.01	.01
fct:sample:linear:loading:items	.01	.01	.01	.00	.01	.00	.00	.00	.00	.00	.00	.00
fct:sample:loading:balance:f_cor	.00	.01	.01	.00	.01	.01	.01	.00	.00	.00	.00	.00
fct:sample:loading:items:balance	.01	.01	.01	.01	.01	.01	.01	.01	.02	.00	.01	.01
fct:sample:loading:items:f_cor	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01
linear:loading:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:linear:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:linear:loading:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:linear:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:linear:loading:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:loading:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:linear:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:linear:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:linear:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:linear:loading:balance	.00	.00	.00	.00	.01	.00	.00	.01	.01	.00	.00	.00
responses:sample:linear:loading:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:linear:loading:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:loading:balance:f_cor	.00	.01	.01	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:loading:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:linear:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:linear:loading:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:linear:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:linear:loading:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:loading:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:linear:loading:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:linear:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:linear:loading:balance:f_cor	.00	.00	.00	.00	.00	.00	.01	.00	.00	.01	.00	.00
fct:responses:linear:loading:items:balance	.01	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:linear:loading:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:loading:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.01	.00	.00	.00	.00	.01
fct:responses:sample:items:balance:f_cor	.01	.01	.01	.01	.01	.00	.01	.01	.01	.00	.01	.01
fct:responses:sample:linear:balance:f_cor	.00	.01	.01	.00	.01	.01	.00	.01	.00	.00	.00	.00
fct:responses:sample:linear:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.01
fct:responses:sample:linear:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:sample:linear:loading:balance	.01	.01	.01	.01	.01	.00	.01	.01	.01	.00	.01	.01
fct:responses:sample:linear:loading:f_cor	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01
fct:responses:sample:linear:loading:items	.01	.01	.01	.01	.01	.01	.01	.01	.00	.01	.00	.01
fct:responses:sample:loading:balance:f_cor	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01
fct:responses:sample:loading:items:balance	.01	.02	.01	.01	.01	.01	.02	.01	.01	.01	.01	.01
fct:responses:sample:loading:items:f_cor	.01	.01	.01	.01	.01	.01	.01	.01	.01	.00	.00	.00
fct:sample:linear:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:sample:linear:loading:balance:f_cor	.00	.01	.01	.00	.01	.01	.00	.01	.01	.00	.00	.00
fct:sample:linear:loading:items:balance	.00	.01	.00	.00	.01	.00	.00	.01	.01	.01	.00	.01
fct:sample:linear:loading:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.01	.01	.00	.00	.00
fct:sample:loading:items:balance:f_cor	.01	.01	.01	.01	.01	.01	.00	.01	.01	.00	.01	.01

responses:linear:loading:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:linear:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:linear:loading:balance:f_cor	.00	.00	.00	.01	.01	.00	.01	.00	.00	.00	.00	.00
responses:sample:linear:loading:items:balance	.01	.01	.01	.00	.01	.01	.00	.01	.01	.01	.01	.01
responses:sample:linear:loading:items:f_cor	.00	.01	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:loading:items:balance:f_cor	.01	.00	.00	.01	.00	.00	.01	.00	.00	.00	.00	.00
sample:linear:loading:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.01
fct:responses:linear:loading:items:balance:f_cor	.01	.00	.01	.01	.00	.00	.01	.00	.00	.00	.00	.00
fct:responses:sample:linear:items:balance:f_cor	.00	.01	.00	.00	.01	.00	.01	.01	.01	.00	.01	.01
fct:responses:sample:linear:loading:balance:f_cor	.01	.01	.01	.01	.01	.01	.02	.01	.01	.01	.01	.01
fct:responses:sample:linear:loading:items:balance	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01
fct:responses:sample:linear:loading:items:f_cor	.01	.00	.01	.01	.01	.01	.01	.01	.01	.01	.01	.00
fct:responses:sample:loading:items:balance:f_cor	.02	.02	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01
fct:sample:linear:loading:items:balance:f_cor	.01	.00	.01	.01	.00	.01	.01	.01	.01	.00	.00	.00
responses:sample:linear:loading:items:balance:f_cor	.00	.00	.01	.01	.01	.01	.00	.00	.00	.00	.00	.00
fct:responses:sample:linear:loading:items:balance:f_cor	.01	.01	.02	.02	.02	.01	.01	.01	.01	.01	.02	.02

Table 31. Accuracy Partial Eta Squared by Term Interaction (Part 4)

Term	walktrap_log_bic	louvain_log_bic	leiden_log_bic	walktrap_log_gic_3	louvain_log_gic_3	leiden_log_gic_3	walktrap_log_gic_4	louvain_log_gic_4	leiden_log_gic_4	walktrap_log_ebic	louvain_log_ebic	leiden_log_ebic
balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor	.13	.09	.09	.13	.08	.09	.12	.09	.09	.10	.07	.06
fct	.11	.04	.04	.11	.04	.05	.08	.04	.04	.05	.02	.02
items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
linear	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
loading	.32	.28	.28	.32	.28	.30	.41	.38	.39	.53	.53	.53
responses	.12	.10	.10	.11	.08	.08	.04	.04	.04	.02	.02	.02
sample	.21	.22	.22	.20	.20	.22	.23	.24	.24	.29	.29	.29
balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:balance	.00	.01	.01	.00	.01	.01	.00	.01	.01	.01	.01	.01
fct:f_cor	.03	.01	.01	.04	.01	.02	.03	.01	.01	.02	.01	.01
fct:items	.01	.06	.07	.02	.07	.08	.02	.06	.06	.02	.04	.04
fct:linear	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:loading	.01	.00	.00	.02	.00	.01	.03	.02	.01	.02	.01	.01
fct:responses	.02	.01	.01	.01	.01	.01	.00	.02	.02	.00	.01	.01
fct:sample	.00	.01	.01	.00	.01	.01	.00	.01	.01	.00	.00	.00
items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
items:f_cor	.01	.00	.00	.01	.00	.00	.00	.00	.00	.00	.00	.00
linear:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
linear:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
linear:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
linear:loading	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.01	.01
loading:f_cor	.04	.02	.03	.04	.02	.02	.03	.02	.02	.02	.01	.01
loading:items	.00	.00	.00	.01	.01	.00	.01	.01	.01	.00	.00	.00
responses:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.01	.01	.01	.00
responses:items	.00	.01	.01	.00	.01	.01	.00	.01	.01	.00	.00	.00
responses:linear	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:loading	.01	.01	.00	.01	.01	.01	.00	.00	.00	.00	.01	.01
responses:sample	.04	.03	.03	.03	.02	.02	.01	.00	.00	.00	.00	.00
sample:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00

sample:f_cor	.00	.00	.00	.01	.00	.01	.00	.00	.00	.00	.00	.00
sample:items	.01	.02	.02	.02	.02	.02	.02	.02	.02	.01	.01	.01
sample:linear	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:loading	.03	.04	.05	.04	.05	.06	.10	.10	.11	.18	.18	.18
fct:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:items:f_cor	.01	.01	.01	.01	.01	.01	.01	.02	.01	.00	.01	.01
fct:linear:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:linear:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:linear:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:linear:loading	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:loading:balance	.00	.01	.01	.00	.01	.01	.00	.00	.01	.00	.00	.00
fct:loading:f_cor	.01	.00	.00	.01	.00	.00	.01	.00	.00	.01	.00	.00
fct:loading:items	.01	.01	.01	.01	.01	.01	.00	.01	.01	.00	.01	.01
fct:responses:balance	.00	.00	.00	.00	.00	.00	.00	.00	.01	.00	.00	.00
fct:responses:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:items	.00	.01	.01	.00	.01	.01	.00	.01	.01	.00	.01	.01
fct:responses:linear	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:loading	.01	.02	.01	.01	.02	.02	.01	.01	.01	.00	.00	.00
fct:responses:sample	.01	.01	.01	.00	.00	.00	.01	.01	.01	.01	.01	.01
fct:sample:balance	.00	.01	.01	.00	.01	.01	.00	.01	.01	.00	.00	.00
fct:sample:f_cor	.00	.00	.00	.00	.00	.00	.00	.01	.00	.00	.00	.00
fct:sample:items	.00	.01	.01	.01	.01	.01	.01	.01	.01	.00	.00	.00
fct:sample:linear	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:sample:loading	.03	.02	.03	.02	.02	.02	.01	.02	.01	.01	.01	.01
items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
linear:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
linear:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
linear:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
linear:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
linear:loading:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
linear:loading:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
loading:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
loading:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:linear:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:linear:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:linear:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:linear:loading	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:loading:f_cor	.00	.00	.00	.01	.00	.00	.00	.00	.00	.00	.00	.00
responses:loading:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:items	.00	.01	.01	.00	.00	.01	.00	.00	.00	.00	.00	.00
responses:sample:linear	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:loading	.04	.06	.04	.05	.05	.05	.04	.04	.05	.02	.02	.02
sample:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:linear:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:linear:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:linear:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:linear:loading	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.01

sample:loading:f_cor	.03	.02	.02	.03	.03	.02	.04	.04	.04	.05	.04	.04
sample:loading:items	.01	.01	.01	.02	.01	.02	.02	.02	.02	.01	.01	.01
fct:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:linear:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:linear:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:linear:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:linear:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:linear:loading:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:linear:loading:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:loading:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:loading:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:balance:f_cor	.01	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:linear:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:linear:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:linear:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:linear:loading	.01	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.01	.00	.00
fct:responses:loading:f_cor	.01	.00	.00	.01	.01	.01	.01	.00	.00	.01	.01	.00
fct:responses:loading:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.01	.00	.00
fct:responses:sample:balance	.00	.00	.00	.00	.00	.00	.00	.01	.01	.01	.01	.01
fct:responses:sample:f_cor	.01	.01	.01	.00	.01	.00	.01	.01	.01	.01	.01	.01
fct:responses:sample:items	.00	.01	.01	.01	.01	.01	.01	.00	.01	.00	.00	.00
fct:responses:sample:linear	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:sample:loading	.01	.01	.01	.01	.01	.01	.01	.01	.01	.02	.01	.01
fct:sample:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:sample:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:sample:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:sample:linear:balance	.00	.00	.00	.00	.00	.00	.00	.01	.00	.00	.00	.00
fct:sample:linear:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:sample:linear:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:sample:linear:loading	.00	.00	.00	.01	.01	.01	.01	.00	.01	.00	.01	.01
fct:sample:loading:balance	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01
fct:sample:loading:f_cor	.01	.00	.00	.01	.01	.01	.02	.01	.01	.01	.00	.01
fct:sample:loading:items	.01	.01	.01	.00	.01	.01	.00	.01	.01	.00	.01	.02
linear:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
linear:loading:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
linear:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
linear:loading:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
loading:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:linear:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:linear:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:linear:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:linear:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:linear:loading:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:linear:loading:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:loading:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:loading:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:linear:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:linear:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:linear:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00

responses:sample:linear:loading	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:loading:balance	.00	.01	.01	.00	.00	.01	.00	.01	.01	.00	.00	.00
responses:sample:loading:f_cor	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01
responses:sample:loading:items	.01	.01	.00	.00	.00	.00	.00	.00	.00	.01	.01	.01
sample:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:linear:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:linear:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:linear:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:linear:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:linear:loading:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:linear:loading:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:loading:balance:f_cor	.00	.00	.00	.00	.00	.01	.00	.00	.00	.00	.00	.00
sample:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:loading:items:f_cor	.01	.01	.01	.01	.01	.01	.01	.01	.01	.00	.00	.00
fct:linear:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:linear:loading:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:linear:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:linear:loading:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:loading:items:balance:f_cor	.00	.00	.00	.00	.01	.01	.00	.01	.00	.00	.00	.00
fct:responses:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:linear:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:linear:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:linear:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:linear:loading:balance	.00	.00	.00	.00	.01	.01	.00	.01	.00	.00	.00	.00
fct:responses:linear:loading:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.01	.00	.00
fct:responses:linear:loading:items	.00	.00	.00	.00	.00	.00	.01	.01	.00	.00	.00	.00
fct:responses:loading:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:loading:items:balance	.00	.01	.00	.00	.00	.01	.00	.00	.00	.01	.00	.00
fct:responses:loading:items:f_cor	.00	.00	.00	.00	.01	.00	.00	.00	.00	.00	.00	.00
fct:responses:sample:balance:f_cor	.01	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:sample:items:balance	.01	.00	.00	.00	.01	.00	.01	.01	.00	.01	.01	.01
fct:responses:sample:items:f_cor	.00	.00	.00	.01	.01	.00	.00	.00	.01	.00	.01	.00
fct:responses:sample:linear:balance	.00	.01	.01	.00	.01	.01	.01	.01	.00	.01	.00	.00
fct:responses:sample:linear:f_cor	.01	.01	.00	.01	.01	.01	.00	.00	.00	.00	.00	.00
fct:responses:sample:linear:items	.00	.00	.00	.00	.00	.00	.01	.00	.00	.00	.00	.00
fct:responses:sample:linear:loading	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01
fct:responses:sample:loading:balance	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01
fct:responses:sample:loading:f_cor	.01	.01	.01	.01	.01	.01	.01	.02	.02	.01	.02	.01
fct:responses:sample:loading:items	.01	.01	.02	.01	.01	.01	.02	.01	.01	.02	.01	.01
fct:sample:items:balance:f_cor	.00	.01	.01	.00	.00	.01	.00	.01	.00	.00	.00	.00
fct:sample:linear:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:sample:linear:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:sample:linear:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:sample:linear:loading:balance	.00	.00	.00	.00	.00	.00	.00	.01	.00	.00	.01	.01
fct:sample:linear:loading:f_cor	.01	.00	.01	.01	.00	.00	.00	.00	.00	.01	.00	.00
fct:sample:linear:loading:items	.00	.01	.00	.00	.01	.01	.00	.00	.01	.00	.00	.00
fct:sample:loading:balance:f_cor	.00	.01	.01	.00	.01	.01	.00	.00	.00	.00	.00	.00
fct:sample:loading:items:balance	.00	.01	.01	.00	.01	.01	.01	.01	.01	.01	.01	.01
fct:sample:loading:items:f_cor	.01	.01	.01	.00	.01	.01	.01	.01	.01	.01	.01	.01
linear:loading:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:linear:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:linear:loading:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:linear:loading:items:balance	.00	.00	.00	.00	.01	.00	.00	.00	.00	.00	.00	.00
responses:linear:loading:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:loading:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:linear:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:linear:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00

responses:sample:linear:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:linear:loading:balance	.00	.00	.00	.00	.00	.01	.00	.01	.00	.00	.00	.00
responses:sample:linear:loading:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:linear:loading:items	.00	.00	.00	.01	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:loading:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.01	.00	.00	.00	.00
responses:sample:loading:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.01	.00
sample:linear:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:linear:loading:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:linear:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:linear:loading:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:loading:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:linear:loading:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:linear:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:linear:loading:balance:f_cor	.00	.00	.00	.00	.00	.00	.01	.00	.00	.00	.00	.00
fct:responses:linear:loading:items:balance	.00	.00	.01	.01	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:linear:loading:items:f_cor	.00	.00	.00	.00	.00	.01	.00	.00	.00	.00	.00	.00
fct:responses:loading:items:balance:f_cor	.00	.00	.00	.00	.01	.00	.01	.00	.00	.00	.00	.00
fct:responses:sample:items:balance:f_cor	.00	.01	.01	.00	.00	.00	.01	.01	.00	.00	.01	.01
fct:responses:sample:linear:balance:f_cor	.00	.01	.01	.01	.00	.01	.01	.00	.01	.01	.01	.00
fct:responses:sample:linear:items:balance	.01	.00	.01	.00	.01	.00	.00	.00	.00	.00	.01	.01
fct:responses:sample:linear:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:sample:linear:loading:balance	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01
fct:responses:sample:linear:loading:f_cor	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01
fct:responses:sample:linear:loading:items	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01	.00	.01
fct:responses:sample:loading:balance:f_cor	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01	.00	.01
fct:responses:sample:loading:items:balance	.01	.01	.02	.01	.01	.01	.01	.01	.01	.01	.01	.01
fct:responses:sample:loading:items:f_cor	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01	.00
fct:sample:linear:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:sample:linear:loading:balance:f_cor	.00	.00	.00	.01	.00	.01	.00	.00	.01	.00	.01	.00
fct:sample:linear:loading:items:balance	.00	.01	.01	.00	.01	.00	.00	.01	.01	.01	.00	.00
fct:sample:linear:loading:items:f_cor	.00	.01	.00	.00	.00	.01	.00	.00	.01	.00	.01	.01
fct:sample:loading:items:balance:f_cor	.00	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01
responses:linear:loading:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:linear:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:linear:loading:balance:f_cor	.00	.00	.00	.00	.01	.01	.00	.00	.00	.00	.00	.00
responses:sample:linear:loading:items:balance	.00	.00	.01	.00	.01	.01	.00	.01	.01	.01	.01	.01
responses:sample:linear:loading:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.01	.00
responses:sample:loading:items:balance:f_cor	.01	.00	.00	.01	.00	.00	.00	.00	.00	.00	.00	.00
sample:linear:loading:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:linear:loading:items:balance:f_cor	.00	.00	.00	.01	.00	.00	.00	.00	.01	.01	.00	.00
fct:responses:sample:linear:items:balance:f_cor	.00	.01	.01	.00	.00	.00	.00	.01	.01	.00	.00	.00
fct:responses:sample:linear:loading:balance:f_cor	.01	.01	.01	.01	.01	.01	.01	.01	.02	.01	.01	.01
fct:responses:sample:linear:loading:items:balance	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01
fct:responses:sample:linear:loading:items:f_cor	.01	.00	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01
fct:responses:sample:loading:items:balance:f_cor	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01
fct:sample:linear:loading:items:balance:f_cor	.01	.00	.00	.00	.00	.00	.01	.00	.00	.00	.00	.00
responses:sample:linear:loading:items:balance:f_cor	.00	.00	.00	.00	.00	.01	.00	.00	.00	.00	.00	.00
fct:responses:sample:linear:loading:items:balance:f_cor	.01	.01	.01	.02	.01	.01	.01	.01	.01	.01	.01	.02

Table 32. Accuracy Partial Eta Squared by Term Interaction (Part 5)

Term	R2Z_walktrap	R2Z_louvain	R2Z_leiden	fspe	EGAnet	PA_FA	PA_PC

balance	.00	.00	.00	.01	.00	.00	.00
f_cor	.18	.08	.07	.22	.20	.09	.47
fct	.46	.26	.26	.08	.07	.03	.13
items	.00	.00	.01	.05	.04	.01	.10
linear	.00	.00	.00	.00	.00	.00	.00
loading	.50	.30	.31	.43	.38	.60	.26
responses	.07	.04	.03	.08	.02	.45	.02
sample	.40	.22	.23	.18	.14	.13	.11
balance:f_cor	.00	.00	.00	.00	.00	.00	.00
fct:balance	.00	.01	.00	.00	.00	.00	.00
fct:f_cor	.02	.02	.01	.03	.03	.03	.02
fct:items	.00	.08	.08	.01	.01	.01	.00
fct:linear	.00	.00	.00	.00	.00	.00	.00
fct:loading	.09	.05	.05	.05	.03	.01	.01
fct:responses	.00	.00	.00	.00	.00	.00	.00
fct:sample	.06	.03	.03	.02	.00	.01	.01
items:balance	.00	.00	.00	.00	.00	.00	.00
items:f_cor	.00	.00	.00	.00	.03	.00	.09
linear:balance	.00	.00	.00	.00	.00	.00	.00
linear:f_cor	.00	.00	.00	.00	.00	.00	.00
linear:items	.00	.00	.00	.00	.00	.00	.00
linear:loading	.00	.00	.00	.00	.00	.00	.00
loading:balance	.00	.00	.00	.00	.00	.01	.00
loading:f_cor	.01	.00	.00	.10	.03	.01	.01
loading:items	.01	.00	.00	.02	.01	.04	.01
responses:balance	.00	.00	.00	.00	.00	.02	.00
responses:f_cor	.00	.00	.00	.01	.00	.00	.05
responses:items	.00	.00	.00	.00	.00	.10	.02
responses:linear	.00	.00	.00	.00	.00	.00	.00
responses:loading	.00	.00	.00	.02	.00	.16	.03
responses:sample	.00	.00	.00	.00	.00	.00	.00
sample:balance	.00	.00	.00	.00	.00	.00	.00
sample:f_cor	.00	.00	.00	.01	.00	.02	.00
sample:items	.02	.02	.02	.00	.00	.00	.00
sample:linear	.00	.00	.00	.00	.00	.00	.00
sample:loading	.05	.03	.03	.07	.08	.01	.02
fct:balance:f_cor	.00	.00	.00	.00	.00	.00	.00
fct:items:balance	.00	.00	.00	.00	.00	.00	.00
fct:items:f_cor	.00	.01	.01	.00	.00	.01	.00
fct:linear:balance	.00	.00	.00	.00	.00	.00	.00
fct:linear:f_cor	.00	.00	.00	.00	.00	.00	.00
fct:linear:items	.00	.00	.00	.00	.00	.00	.00
fct:linear:loading	.00	.00	.00	.00	.00	.00	.00
fct:loading:balance	.00	.01	.01	.00	.00	.00	.00
fct:loading:f_cor	.03	.01	.01	.01	.01	.00	.01
fct:loading:items	.01	.03	.04	.00	.00	.02	.00
fct:responses:balance	.00	.00	.00	.00	.00	.00	.00
fct:responses:f_cor	.00	.00	.00	.00	.00	.00	.01
fct:responses:items	.00	.00	.00	.00	.00	.00	.00
fct:responses:linear	.00	.00	.00	.00	.00	.00	.00
fct:responses:loading	.01	.01	.01	.01	.00	.01	.00
fct:responses:sample	.01	.01	.01	.00	.00	.01	.00
fct:sample:balance	.00	.00	.00	.00	.00	.00	.00
fct:sample:f_cor	.01	.00	.00	.00	.00	.01	.00
fct:sample:items	.01	.01	.01	.00	.00	.00	.00
fct:sample:linear	.00	.00	.01	.00	.00	.00	.00
fct:sample:loading	.11	.03	.03	.01	.02	.01	.00
items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00

linear:balance:f_cor	.00	.00	.00	.00	.00	.00	.00
linear:items:balance	.00	.00	.00	.00	.00	.00	.00
linear:items:f_cor	.00	.00	.00	.00	.00	.00	.00
linear:loading:balance	.00	.00	.00	.00	.00	.00	.00
linear:loading:f_cor	.00	.00	.00	.00	.00	.00	.00
linear:loading:items	.00	.00	.00	.00	.00	.00	.00
loading:balance:f_cor	.00	.00	.00	.00	.00	.00	.00
loading:items:balance	.00	.00	.00	.00	.00	.00	.00
loading:items:f_cor	.01	.00	.00	.01	.02	.00	.01
responses:balance:f_cor	.00	.00	.00	.00	.00	.00	.00
responses:items:balance	.00	.00	.00	.00	.00	.00	.00
responses:items:f_cor	.00	.00	.00	.00	.00	.00	.00
responses:linear:balance	.00	.00	.00	.00	.00	.00	.00
responses:linear:f_cor	.00	.00	.00	.00	.00	.00	.00
responses:linear:items	.00	.00	.00	.00	.00	.00	.00
responses:linear:loading	.00	.00	.00	.00	.00	.00	.00
responses:loading:balance	.00	.00	.00	.00	.00	.00	.00
responses:loading:f_cor	.01	.01	.01	.01	.00	.02	.04
responses:loading:items	.00	.00	.00	.00	.00	.03	.03
responses:sample:balance	.00	.00	.00	.00	.00	.00	.00
responses:sample:f_cor	.01	.00	.00	.00	.00	.01	.01
responses:sample:items	.00	.00	.00	.00	.00	.00	.00
responses:sample:linear	.00	.00	.00	.00	.00	.00	.00
responses:sample:loading	.02	.00	.01	.01	.02	.04	.01
sample:balance:f_cor	.00	.00	.00	.00	.00	.00	.00
sample:items:balance	.00	.00	.00	.00	.00	.00	.00
sample:items:f_cor	.00	.00	.00	.00	.00	.00	.01
sample:linear:balance	.00	.00	.00	.00	.00	.00	.00
sample:linear:f_cor	.00	.00	.00	.00	.00	.00	.00
sample:linear:items	.00	.00	.00	.00	.00	.00	.00
sample:linear:loading	.00	.00	.00	.00	.00	.00	.00
sample:loading:balance	.00	.00	.00	.00	.00	.00	.00
sample:loading:f_cor	.04	.03	.03	.04	.05	.01	.02
sample:loading:items	.01	.01	.01	.00	.01	.01	.00
fct:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00
fct:linear:balance:f_cor	.00	.00	.00	.00	.00	.00	.00
fct:linear:items:balance	.00	.00	.00	.00	.00	.00	.00
fct:linear:items:f_cor	.00	.00	.00	.00	.00	.00	.00
fct:linear:loading:balance	.00	.00	.00	.00	.00	.00	.00
fct:linear:loading:f_cor	.00	.00	.00	.00	.00	.00	.00
fct:linear:loading:items	.00	.00	.00	.00	.00	.00	.00
fct:loading:balance:f_cor	.00	.00	.00	.00	.00	.00	.00
fct:loading:items:balance	.00	.00	.00	.00	.00	.00	.00
fct:loading:items:f_cor	.00	.00	.00	.00	.00	.00	.00
fct:responses:balance:f_cor	.00	.00	.00	.00	.00	.00	.00
fct:responses:items:balance	.00	.00	.00	.00	.00	.00	.00
fct:responses:items:f_cor	.00	.00	.00	.00	.00	.00	.00
fct:responses:linear:balance	.00	.00	.00	.00	.00	.00	.00
fct:responses:linear:f_cor	.00	.00	.00	.00	.00	.00	.00
fct:responses:linear:items	.00	.00	.00	.00	.00	.00	.00
fct:responses:linear:loading	.00	.00	.00	.00	.00	.00	.00
fct:responses:loading:balance	.00	.01	.01	.00	.00	.00	.00
fct:responses:loading:f_cor	.00	.01	.01	.01	.00	.02	.01
fct:responses:loading:items	.00	.01	.01	.00	.00	.01	.00
fct:responses:sample:balance	.00	.00	.00	.01	.00	.01	.00
fct:responses:sample:f_cor	.00	.00	.00	.00	.00	.00	.00
fct:responses:sample:items	.01	.01	.00	.00	.00	.00	.00
fct:responses:sample:linear	.00	.00	.00	.00	.00	.00	.00

fct:responses:sample:loading	.02	.01	.01	.01	.01	.01	.01
fct:sample:balance:f_cor	.00	.00	.01	.00	.00	.00	.00
fct:sample:items:balance	.00	.00	.00	.00	.00	.00	.00
fct:sample:items:f_cor	.00	.00	.00	.00	.00	.00	.00
fct:sample:linear:balance	.00	.00	.00	.00	.00	.00	.00
fct:sample:linear:f_cor	.00	.00	.00	.00	.00	.00	.00
fct:sample:linear:items	.00	.00	.00	.00	.00	.00	.00
fct:sample:linear:loading	.00	.01	.01	.00	.00	.00	.00
fct:sample:loading:balance	.00	.01	.00	.01	.01	.01	.00
fct:sample:loading:f_cor	.04	.01	.01	.02	.01	.01	.01
fct:sample:loading:items	.01	.01	.01	.00	.00	.00	.00
linear:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00
linear:loading:balance:f_cor	.00	.00	.00	.00	.00	.00	.00
linear:loading:items:balance	.00	.00	.00	.00	.00	.00	.00
linear:loading:items:f_cor	.00	.00	.00	.00	.00	.00	.00
loading:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00
responses:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00
responses:linear:balance:f_cor	.00	.00	.00	.00	.00	.00	.00
responses:linear:items:balance	.00	.00	.00	.00	.00	.00	.00
responses:linear:items:f_cor	.00	.00	.00	.00	.00	.00	.00
responses:linear:loading:balance	.00	.00	.00	.00	.00	.00	.00
responses:linear:loading:f_cor	.00	.00	.00	.00	.00	.00	.00
responses:linear:loading:items	.00	.00	.00	.00	.00	.00	.00
responses:loading:balance:f_cor	.00	.00	.00	.00	.00	.00	.00
responses:loading:items:balance	.00	.00	.00	.00	.00	.00	.00
responses:loading:items:f_cor	.00	.00	.00	.00	.00	.01	.00
responses:sample:balance:f_cor	.00	.00	.00	.00	.00	.00	.00
responses:sample:items:balance	.00	.00	.00	.00	.00	.00	.00
responses:sample:items:f_cor	.00	.00	.00	.00	.00	.00	.00
responses:sample:linear:balance	.00	.00	.00	.00	.00	.00	.00
responses:sample:linear:f_cor	.00	.00	.00	.00	.00	.00	.00
responses:sample:linear:items	.00	.00	.00	.00	.00	.00	.00
responses:sample:linear:loading	.00	.00	.01	.00	.00	.01	.00
responses:sample:loading:balance	.00	.00	.00	.00	.00	.00	.00
responses:sample:loading:f_cor	.01	.00	.01	.02	.00	.03	.01
responses:sample:loading:items	.00	.00	.00	.00	.00	.01	.00
sample:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00
sample:linear:balance:f_cor	.00	.00	.00	.00	.00	.00	.00
sample:linear:items:balance	.00	.00	.00	.00	.00	.00	.00
sample:linear:items:f_cor	.00	.00	.00	.00	.00	.00	.00
sample:linear:loading:balance	.00	.00	.01	.00	.00	.00	.00
sample:linear:loading:f_cor	.00	.00	.00	.00	.00	.00	.00
sample:linear:loading:items	.00	.00	.00	.00	.00	.00	.00
sample:loading:balance:f_cor	.00	.00	.00	.00	.00	.00	.00
sample:loading:items:balance	.00	.00	.00	.00	.00	.00	.00
sample:loading:items:f_cor	.00	.00	.00	.01	.01	.00	.00
fct:linear:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00
fct:linear:loading:balance:f_cor	.00	.00	.00	.00	.00	.00	.00
fct:linear:loading:items:balance	.00	.00	.00	.00	.00	.00	.00
fct:linear:loading:items:f_cor	.00	.00	.00	.00	.00	.00	.00
fct:loading:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00
fct:responses:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00
fct:responses:linear:balance:f_cor	.00	.00	.00	.00	.00	.00	.00
fct:responses:linear:items:balance	.00	.00	.00	.00	.00	.00	.00
fct:responses:linear:items:f_cor	.00	.00	.00	.00	.00	.00	.00
fct:responses:linear:loading:balance	.00	.00	.01	.00	.00	.00	.00
fct:responses:linear:loading:f_cor	.00	.00	.00	.01	.00	.00	.00
fct:responses:linear:loading:items	.00	.00	.00	.00	.00	.00	.00

fct:responses:loading:balance:f_cor	.00	.00	.00	.00	.00	.00	.00
fct:responses:loading:items:balance	.00	.00	.00	.00	.00	.00	.00
fct:responses:loading:items:f_cor	.00	.00	.00	.00	.00	.00	.00
fct:responses:sample:balance:f_cor	.00	.00	.01	.01	.00	.00	.00
fct:responses:sample:items:balance	.01	.00	.01	.01	.00	.00	.01
fct:responses:sample:items:f_cor	.00	.00	.00	.00	.00	.00	.00
fct:responses:sample:linear:balance	.00	.00	.00	.01	.00	.00	.00
fct:responses:sample:linear:f_cor	.00	.00	.00	.00	.00	.00	.00
fct:responses:sample:linear:items	.00	.01	.00	.01	.00	.01	.00
fct:responses:sample:linear:loading	.01	.01	.01	.01	.01	.01	.01
fct:responses:sample:loading:balance	.01	.01	.01	.01	.01	.01	.01
fct:responses:sample:loading:f_cor	.02	.02	.02	.01	.01	.03	.01
fct:responses:sample:loading:items	.01	.01	.01	.01	.01	.01	.01
fct:sample:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00
fct:sample:linear:balance:f_cor	.00	.00	.00	.00	.00	.00	.00
fct:sample:linear:items:balance	.00	.00	.00	.00	.00	.01	.00
fct:sample:linear:items:f_cor	.00	.00	.00	.00	.00	.00	.00
fct:sample:linear:loading:balance	.00	.00	.00	.01	.01	.00	.00
fct:sample:linear:loading:f_cor	.01	.01	.01	.00	.00	.00	.00
fct:sample:linear:loading:items	.00	.00	.00	.00	.01	.01	.00
fct:sample:loading:balance:f_cor	.00	.01	.01	.01	.00	.00	.00
fct:sample:loading:items:balance	.00	.00	.00	.00	.00	.00	.00
fct:sample:loading:items:f_cor	.01	.01	.01	.01	.00	.00	.00
linear:loading:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00
responses:linear:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00
responses:linear:loading:balance:f_cor	.00	.00	.00	.00	.00	.00	.00
responses:linear:loading:items:balance	.00	.00	.00	.00	.00	.00	.00
responses:linear:loading:items:f_cor	.00	.00	.00	.00	.00	.00	.00
responses:loading:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00
responses:sample:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00
responses:sample:linear:balance:f_cor	.00	.00	.00	.00	.00	.00	.00
responses:sample:linear:items:balance	.00	.00	.00	.00	.00	.00	.00
responses:sample:linear:items:f_cor	.00	.00	.00	.00	.00	.00	.00
responses:sample:linear:loading:balance	.00	.00	.00	.00	.00	.01	.00
responses:sample:linear:loading:f_cor	.00	.01	.01	.00	.00	.00	.00
responses:sample:linear:loading:items	.00	.00	.00	.00	.00	.00	.00
responses:sample:loading:balance:f_cor	.00	.00	.00	.00	.00	.00	.00
responses:sample:loading:items:balance	.00	.00	.00	.00	.00	.00	.01
responses:sample:loading:items:f_cor	.00	.00	.00	.01	.00	.00	.00
sample:linear:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00
sample:linear:loading:balance:f_cor	.00	.00	.00	.00	.00	.00	.00
sample:linear:loading:items:balance	.00	.00	.00	.00	.00	.00	.00
sample:linear:loading:items:f_cor	.00	.00	.00	.00	.00	.00	.00
sample:loading:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00
fct:linear:loading:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00
fct:responses:linear:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00
fct:responses:linear:loading:balance:f_cor	.00	.00	.00	.00	.00	.00	.00
fct:responses:linear:loading:items:balance	.00	.00	.00	.00	.01	.00	.00
fct:responses:linear:loading:items:f_cor	.00	.00	.00	.00	.00	.00	.00
fct:responses:loading:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00
fct:responses:sample:items:balance:f_cor	.01	.01	.01	.00	.00	.01	.00
fct:responses:sample:linear:balance:f_cor	.01	.01	.01	.00	.00	.00	.00
fct:responses:sample:linear:items:balance	.01	.01	.00	.00	.01	.01	.00
fct:responses:sample:linear:items:f_cor	.01	.00	.01	.01	.00	.01	.00
fct:responses:sample:linear:loading:balance	.01	.01	.01	.01	.01	.01	.01
fct:responses:sample:linear:loading:f_cor	.01	.01	.01	.01	.01	.01	.01
fct:responses:sample:linear:loading:items	.01	.01	.01	.01	.01	.02	.00
fct:responses:sample:loading:balance:f_cor	.01	.01	.01	.01	.01	.01	.00

fct:responses:sample:loading:items:balance	.01	.01	.01	.01	.01	.01	.01
fct:responses:sample:loading:items:f_cor	.01	.01	.01	.01	.01	.01	.00
fct:sample:linear:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00
fct:sample:linear:loading:balance:f_cor	.00	.00	.01	.00	.00	.01	.00
fct:sample:linear:loading:items:balance	.01	.00	.00	.01	.00	.00	.00
fct:sample:linear:loading:items:f_cor	.00	.01	.00	.01	.00	.00	.00
fct:sample:loading:items:balance:f_cor	.01	.00	.00	.01	.01	.01	.00
responses:linear:loading:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00
responses:sample:linear:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00
responses:sample:linear:loading:balance:f_cor	.00	.00	.00	.00	.00	.01	.00
responses:sample:linear:loading:items:balance	.00	.00	.00	.01	.00	.01	.00
responses:sample:linear:loading:items:f_cor	.00	.00	.00	.00	.00	.00	.00
responses:sample:loading:items:balance:f_cor	.00	.01	.00	.00	.00	.00	.00
sample:linear:loading:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00
fct:responses:linear:loading:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00
fct:responses:sample:linear:items:balance:f_cor	.00	.01	.01	.01	.01	.01	.00
fct:responses:sample:linear:loading:balance:f_cor	.01	.01	.01	.01	.01	.01	.01
fct:responses:sample:linear:loading:items:balance	.01	.01	.01	.01	.01	.02	.01
fct:responses:sample:linear:loading:items:f_cor	.01	.01	.01	.01	.01	.01	.00
fct:responses:sample:loading:items:balance:f_cor	.01	.02	.02	.01	.01	.01	.01
fct:sample:linear:loading:items:balance:f_cor	.01	.01	.01	.01	.01	.01	.00
responses:sample:linear:loading:items:balance:f_cor	.00	.01	.01	.00	.00	.01	.00
fct:responses:sample:linear:loading:items:balance:f_cor	.01	.01	.01	.01	.01	.01	.01

Table 33. ARI Partial Eta Squared by Term Interaction (Part 1)

Term	**walktrap_atan_bic**	**louvain_atan_bic**	**leiden_atan_bic**	**walktrap_atan_gic_3**	**louvain_atan_gic_3**	**leiden_atan_gic_3**	**walktrap_atan_gic_4**	**louvain_atan_gic_4**	**leiden_atan_gic_4**	**walktrap_atan_ebic**	**louvain_atan_ebic**	**leiden_atan_ebic**
balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor	.22	.20	.20	.22	.21	.19	.24	.22	.21	.24	.23	.22
fct	.05	.03	.03	.05	.02	.02	.04	.01	.01	.03	.01	.01
items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
linear	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
loading	.45	.45	.45	.45	.45	.45	.54	.55	.55	.64	.65	.65
responses	.23	.23	.22	.21	.19	.18	.13	.13	.12	.09	.09	.09
sample	.34	.36	.35	.33	.35	.34	.33	.35	.34	.34	.35	.35
f_cor:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:linear	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:loading	.11	.10	.10	.10	.09	.09	.10	.09	.10	.09	.09	.09
f_cor:responses	.01	.01	.01	.01	.01	.01	.01	.01	.01	.02	.01	.02
f_cor:sample	.00	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01
fct:balance	.00	.00	.00	.00	.00	.00	.00	.00	.01	.00	.00	.00
fct:f_cor	.02	.01	.01	.02	.01	.01	.02	.01	.01	.01	.01	.01
fct:items	.00	.00	.00	.00	.00	.01	.00	.01	.01	.00	.01	.01
fct:linear	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:loading	.00	.00	.00	.01	.00	.00	.01	.01	.01	.01	.01	.01
fct:responses	.02	.01	.01	.01	.00	.00	.00	.00	.00	.00	.00	.00
fct:sample	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
linear:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
linear:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00

linear:loading	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
loading:items	.01	.01	.01	.01	.01	.01	.00	.00	.00	.00	.00	.00
responses:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:items	.01	.01	.01	.00	.01	.01	.00	.00	.00	.00	.00	.00
responses:linear	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:loading	.00	.00	.00	.00	.00	.00	.00	.00	.00	.01	.02	.02
responses:sample	.09	.08	.08	.07	.06	.06	.03	.02	.02	.01	.01	.01
sample:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:items	.01	.01	.01	.01	.01	.01	.01	.01	.00	.01	.01	.00
sample:linear	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:loading	.06	.08	.09	.07	.09	.11	.14	.16	.17	.19	.21	.22
f_cor:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:linear:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:linear:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:linear:loading	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:loading:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:responses:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:responses:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:responses:linear	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:responses:loading	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:responses:sample	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:sample:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:sample:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:sample:linear	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:sample:loading	.02	.02	.02	.02	.02	.02	.04	.03	.03	.05	.05	.04
fct:f_cor:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:linear	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:loading	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:responses	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:sample	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:linear:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:linear:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:linear:loading	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:loading:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:linear	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:loading	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:sample	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:sample:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:sample:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:sample:linear	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:sample:loading	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
linear:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
linear:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
linear:loading:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:linear:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:linear:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:linear:loading	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:loading:items	.01	.01	.01	.01	.01	.01	.00	.00	.00	.00	.00	.00

responses:sample:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:items	.01	.01	.01	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:linear	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:loading	.04	.05	.04	.04	.04	.04	.03	.03	.02	.01	.01	.01
sample:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:linear:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:linear:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:linear:loading	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:loading:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:linear:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:linear:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:linear:loading:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:responses:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:responses:linear:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:responses:linear:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:responses:linear:loading	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:responses:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:responses:loading:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:responses:sample:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:responses:sample:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:responses:sample:linear	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:responses:sample:loading	.01	.01	.01	.00	.01	.01	.01	.01	.01	.01	.01	.01
f_cor:sample:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:sample:linear:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:sample:linear:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:sample:linear:loading	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:sample:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:sample:loading:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:linear:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:linear:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:linear:loading	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:loading:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:responses:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:responses:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:responses:linear	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:responses:loading	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:responses:sample	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:sample:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:sample:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:sample:linear	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:sample:loading	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:linear:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:linear:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:linear:loading:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:linear:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:linear:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:linear:loading	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:loading:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:sample:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:sample:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:sample:linear	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00

fct:responses:sample:loading	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:sample:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:sample:linear:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:sample:linear:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:sample:linear:loading	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:sample:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:sample:loading:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
linear:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:linear:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:linear:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:linear:loading:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:linear:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:linear:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:linear:loading	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:loading:items	.01	.01	.01	.01	.01	.01	.00	.00	.00	.00	.00	.00
sample:linear:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:linear:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:linear:loading:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:linear:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:responses:linear:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:responses:linear:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:responses:linear:loading:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:responses:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:responses:sample:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:responses:sample:linear:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:responses:sample:linear:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:responses:sample:linear:loading	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:responses:sample:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:responses:sample:loading:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:sample:linear:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:sample:linear:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:sample:linear:loading:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:sample:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:linear:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:linear:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:linear:loading:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:responses:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:responses:linear:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:responses:linear:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:responses:linear:loading	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:responses:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:responses:loading:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:responses:sample:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:responses:sample:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:responses:sample:linear	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:responses:sample:loading	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:sample:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:sample:linear:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:sample:linear:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:sample:linear:loading	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:sample:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:sample:loading:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:linear:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00

fct:responses:linear:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:linear:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:linear:loading:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:sample:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:sample:linear:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:sample:linear:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:sample:linear:loading	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:sample:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:sample:loading:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:sample:linear:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:sample:linear:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:sample:linear:loading:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:sample:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:linear:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:linear:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:linear:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:linear:loading:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:linear:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:responses:linear:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:responses:sample:linear:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:responses:sample:linear:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:responses:sample:linear:loading:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:responses:sample:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:sample:linear:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:linear:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:responses:linear:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:responses:linear:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:responses:linear:loading:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:responses:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:responses:sample:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:responses:sample:linear:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:responses:sample:linear:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:responses:sample:linear:loading	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:responses:sample:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:responses:sample:loading:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:sample:linear:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:sample:linear:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:sample:linear:loading:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:sample:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:linear:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:sample:linear:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:sample:linear:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:sample:linear:loading:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:sample:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:sample:linear:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:linear:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:responses:sample:linear:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:responses:linear:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:responses:sample:linear:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:responses:sample:linear:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:responses:sample:linear:loading:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:responses:sample:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:sample:linear:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:sample:linear:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:responses:sample:linear:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00

Table 34. ARI Partial Eta Squared by Term Interaction (Part 2)

Term	walktrap_lasso_bic	louvain_lasso_bic	leiden_lasso_bic	walktrap_lasso_gic_3	louvain_lasso_gic_3	leiden_lasso_gic_3	walktrap_lasso_gic_4	louvain_lasso_gic_4	leiden_lasso_gic_4	walktrap_lasso_ebic	louvain_lasso_ebic	leiden_lasso_ebic
balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor	.20	.15	.14	.20	.15	.14	.20	.15	.14	.17	.13	.13
fct	.06	.03	.03	.05	.03	.03	.05	.03	.04	.06	.05	.05
items	.00	.00	.00	.01	.00	.00	.01	.00	.00	.00	.01	.01
linear	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
loading	.34	.34	.33	.37	.37	.36	.46	.47	.46	.61	.63	.62
responses	.29	.26	.25	.27	.22	.22	.12	.11	.10	.02	.02	.01
sample	.32	.33	.32	.31	.32	.32	.31	.33	.33	.36	.38	.38
f_cor:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:items	.01	.00	.00	.01	.00	.00	.01	.00	.00	.01	.00	.00
f_cor:linear	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:loading	.10	.09	.08	.10	.08	.08	.09	.08	.08	.07	.06	.06
f_cor:responses	.00	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01
f_cor:sample	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01
fct:items	.00	.00	.00	.01	.01	.01	.00	.00	.00	.00	.00	.00
fct:linear	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:loading	.00	.00	.00	.01	.01	.01	.03	.02	.02	.04	.03	.03
fct:responses	.01	.00	.01	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:sample	.00	.00	.00	.00	.00	.00	.00	.01	.01	.00	.00	.00
items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
linear:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
linear:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
linear:loading	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
loading:items	.02	.02	.02	.02	.01	.02	.00	.00	.00	.02	.01	.01
responses:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:items	.01	.02	.02	.00	.01	.01	.00	.00	.00	.01	.01	.01
responses:linear	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:loading	.01	.00	.00	.01	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample	.12	.11	.11	.09	.08	.08	.03	.03	.02	.00	.00	.00
sample:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:items	.01	.01	.01	.01	.01	.01	.00	.01	.01	.01	.01	.01
sample:linear	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:loading	.03	.07	.07	.04	.08	.09	.11	.16	.17	.19	.25	.25
f_cor:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:linear:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:linear:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:linear:loading	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:loading:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:responses:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:responses:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:responses:linear	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:responses:loading	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:responses:sample	.01	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:sample:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00

f_cor:sample:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:sample:linear	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:sample:loading	.01	.01	.01	.02	.01	.01	.03	.02	.02	.07	.05	.05
fct:f_cor:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:linear	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:loading	.00	.00	.00	.00	.00	.00	.01	.00	.00	.00	.00	.00
fct:f_cor:responses	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:sample	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:linear:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:linear:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:linear:loading	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:loading:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:items	.00	.00	.00	.00	.00	.00	.00	.01	.00	.00	.00	.00
fct:responses:linear	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:loading	.01	.01	.01	.01	.01	.01	.00	.01	.00	.00	.00	.00
fct:responses:sample	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:sample:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:sample:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:sample:linear	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:sample:loading	.00	.00	.00	.00	.00	.00	.00	.00	.00	.01	.01	.01
linear:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
linear:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
linear:loading:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:linear:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:linear:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:linear:loading	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:loading:items	.01	.01	.01	.01	.01	.02	.00	.01	.01	.00	.00	.00
responses:sample:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:items	.01	.01	.01	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:linear	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:loading	.06	.06	.06	.07	.07	.06	.05	.05	.05	.02	.01	.01
sample:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:linear:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:linear:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:linear:loading	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:loading:items	.00	.00	.00	.01	.00	.00	.01	.01	.01	.01	.01	.01
f_cor:linear:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:linear:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:linear:loading:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:responses:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:responses:linear:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:responses:linear:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:responses:linear:loading	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:responses:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:responses:loading:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:responses:sample:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:responses:sample:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:responses:sample:linear	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:responses:sample:loading	.01	.01	.01	.00	.01	.01	.00	.01	.01	.00	.00	.00

f_cor:sample:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:sample:linear:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:sample:linear:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:sample:linear:loading	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:sample:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:sample:loading:items	.01	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:linear:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:linear:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:linear:loading	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:loading:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:responses:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:responses:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:responses:linear	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:responses:loading	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:responses:sample	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:sample:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:sample:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:sample:linear	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:sample:loading	.00	.00	.00	.00	.00	.00	.00	.00	.00	.01	.00	.00
fct:linear:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:linear:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:linear:loading:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:linear:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:linear:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:linear:loading	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:loading:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:sample:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:sample:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:sample:linear	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:sample:loading	.00	.00	.00	.01	.01	.01	.01	.01	.01	.00	.00	.00
fct:sample:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:sample:linear:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:sample:linear:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:sample:linear:loading	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:sample:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:sample:loading:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.01	.00	.00
linear:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:linear:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:linear:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:linear:loading:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:linear:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:linear:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:linear:loading	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:loading:items	.01	.01	.01	.01	.01	.01	.00	.00	.00	.00	.00	.00
sample:linear:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:linear:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:linear:loading:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:linear:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:responses:linear:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00

f_cor:responses:linear:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:responses:linear:loading:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:responses:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:responses:sample:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:responses:sample:linear:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:responses:sample:linear:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:responses:sample:linear:loading	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:responses:sample:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:responses:sample:loading:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:sample:linear:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:sample:linear:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:sample:linear:loading:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:sample:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:linear:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:linear:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:linear:loading:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:responses:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:responses:linear:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:responses:linear:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:responses:linear:loading	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:responses:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:responses:loading:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:responses:sample:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:responses:sample:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:responses:sample:linear	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:responses:sample:loading	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:sample:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:sample:linear:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:sample:linear:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:sample:linear:loading	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:sample:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:sample:loading:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:linear:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:linear:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:linear:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:linear:loading:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:sample:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:sample:linear:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:sample:linear:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:sample:linear:loading	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:sample:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:sample:loading:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:sample:linear:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:sample:linear:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:sample:linear:loading:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:sample:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:linear:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:linear:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:linear:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:linear:loading:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:linear:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:responses:linear:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:responses:sample:linear:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:responses:sample:linear:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:responses:sample:linear:loading:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00

f_cor:responses:sample:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:sample:linear:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:linear:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:responses:linear:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:responses:linear:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:responses:linear:loading:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:responses:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:responses:sample:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:responses:sample:linear:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:responses:sample:linear:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:responses:sample:linear:loading	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:responses:sample:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:responses:sample:loading:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:sample:linear:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:sample:linear:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:sample:linear:loading:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:sample:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:linear:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:sample:linear:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:sample:linear:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:sample:linear:loading:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:sample:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:sample:linear:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:linear:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:responses:sample:linear:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:responses:linear:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:responses:sample:linear:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:responses:sample:linear:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:responses:sample:linear:loading:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:responses:sample:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:sample:linear:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:sample:linear:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:responses:sample:linear:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00

Table 35. ARI Partial Eta Squared by Term Interaction (Part 3)

Term	walktrap_adapt_bic	louvain_adapt_bic	leiden_adapt_bic	walktrap_adapt_gic_3	louvain_adapt_gic_3	leiden_adapt_gic_3	walktrap_adapt_gic_4	louvain_adapt_gic_4	leiden_adapt_gic_4	walktrap_adapt_ebic	louvain_adapt_ebic	leiden_adapt_ebic
balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor	.21	.17	.16	.21	.17	.16	.20	.17	.15	.16	.13	.13
fct	.05	.02	.02	.04	.02	.02	.05	.03	.03	.05	.03	.03
items	.01	.00	.00	.01	.00	.00	.01	.00	.00	.00	.00	.00
linear	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
loading	.44	.44	.43	.46	.46	.46	.56	.57	.56	.69	.70	.70
responses	.21	.19	.17	.18	.16	.14	.08	.08	.07	.02	.02	.02
sample	.31	.33	.31	.30	.32	.31	.32	.34	.33	.37	.39	.39
f_cor:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:items	.01	.00	.00	.01	.00	.00	.01	.00	.00	.01	.00	.00
f_cor:linear	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:loading	.10	.10	.09	.10	.09	.09	.09	.08	.07	.05	.05	.05
f_cor:responses	.01	.01	.01	.01	.01	.01	.02	.02	.02	.01	.01	.01

f_cor:sample	.00	.01	.01	.00	.01	.01	.00	.00	.00	.00	.00	.00
fct:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor	.02	.01	.01	.02	.01	.01	.01	.01	.01	.01	.01	.00
fct:items	.00	.01	.00	.00	.01	.01	.01	.01	.01	.00	.00	.00
fct:linear	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:loading	.01	.00	.00	.01	.01	.01	.04	.03	.03	.03	.02	.02
fct:responses	.01	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:sample	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
linear:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
linear:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
linear:loading	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
loading:items	.01	.01	.01	.01	.01	.01	.00	.00	.00	.01	.01	.01
responses:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:items	.00	.01	.01	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:linear	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:loading	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample	.08	.07	.07	.05	.04	.04	.01	.01	.01	.00	.00	.00
sample:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:items	.00	.01	.01	.01	.01	.00	.00	.00	.00	.00	.00	.00
sample:linear	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:loading	.08	.11	.11	.09	.13	.14	.20	.24	.24	.30	.33	.34
f_cor:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:linear:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:linear:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:linear:loading	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:loading:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:responses:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:responses:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:responses:linear	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:responses:loading	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:responses:sample	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:sample:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:sample:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:sample:linear	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:sample:loading	.02	.01	.01	.03	.02	.02	.04	.03	.03	.07	.07	.06
fct:f_cor:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:linear	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:loading	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:responses	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:sample	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:linear:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:linear:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:linear:loading	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:loading:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:linear	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:loading	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:sample	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:sample:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:sample:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:sample:linear	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00

fct:sample:loading	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
linear:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
linear:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
linear:loading:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:linear:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:linear:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:linear:loading	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:loading:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:items	.01	.01	.01	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:linear	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:loading	.04	.04	.04	.04	.04	.04	.03	.03	.03	.02	.02	.02
sample:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:linear:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:linear:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:linear:loading	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:loading:items	.00	.00	.00	.01	.00	.00	.01	.01	.01	.01	.01	.01
f_cor:linear:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:linear:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:linear:loading:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:responses:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:responses:linear:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:responses:linear:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:responses:linear:loading	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:responses:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:responses:loading:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:responses:sample:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:responses:sample:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:responses:sample:linear	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:responses:sample:loading	.01	.01	.01	.01	.01	.01	.00	.01	.01	.00	.01	.01
f_cor:sample:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:sample:linear:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:sample:linear:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:sample:linear:loading	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:sample:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:sample:loading:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:linear:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:linear:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:linear:loading	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:loading:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:responses:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:responses:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:responses:linear	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:responses:loading	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:responses:sample	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:sample:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:sample:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:sample:linear	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:sample:loading	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:linear:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:linear:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00

fct:linear:loading:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:linear:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:linear:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:linear:loading	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:loading:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:sample:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:sample:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:sample:linear	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:sample:loading	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:sample:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:sample:linear:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:sample:linear:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:sample:linear:loading	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:sample:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:sample:loading:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
linear:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:linear:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:linear:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:linear:loading:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:linear:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:linear:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:linear:loading	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:loading:items	.01	.01	.01	.01	.01	.01	.00	.00	.00	.00	.00	.00
sample:linear:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:linear:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:linear:loading:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:linear:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:responses:linear:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:responses:linear:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:responses:linear:loading:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:responses:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:responses:sample:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:responses:sample:linear:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:responses:sample:linear:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:responses:sample:linear:loading	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:responses:sample:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:responses:sample:loading:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:sample:linear:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:sample:linear:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:sample:linear:loading:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:sample:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:linear:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:linear:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:linear:loading:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:responses:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:responses:linear:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:responses:linear:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:responses:linear:loading	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:responses:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:responses:loading:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00

fct:f_cor:responses:sample:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:responses:sample:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:responses:sample:linear	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:responses:sample:loading	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:sample:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:sample:linear:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:sample:linear:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:sample:linear:loading	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:sample:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:sample:loading:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:linear:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:linear:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:linear:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:linear:loading:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:sample:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:sample:linear:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:sample:linear:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:sample:linear:loading	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:sample:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:sample:loading:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:sample:linear:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:sample:linear:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:sample:linear:loading:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:sample:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:linear:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:linear:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:linear:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:linear:loading:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:linear:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:responses:linear:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:responses:sample:linear:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:responses:sample:linear:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:responses:sample:linear:loading:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:responses:sample:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:sample:linear:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:linear:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:responses:linear:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:responses:linear:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:responses:linear:loading:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:responses:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:responses:sample:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:responses:sample:linear:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:responses:sample:linear:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:responses:sample:linear:loading	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:responses:sample:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:responses:sample:loading:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:sample:linear:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:sample:linear:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:sample:linear:loading:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:sample:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:linear:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:sample:linear:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:sample:linear:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:sample:linear:loading:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:sample:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:sample:linear:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00

responses:sample:linear:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:responses:sample:linear:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:responses:linear:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:responses:sample:linear:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:responses:sample:linear:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:responses:sample:linear:loading:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:responses:sample:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:sample:linear:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:sample:linear:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:responses:sample:linear:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00

Table 36. ARI Partial Eta Squared by Term Interaction (Part 4)

Term	walktrap_log_bic	louvain_log_bic	leiden_log_bic	walktrap_log_gic_3	louvain_log_gic_3	leiden_log_gic_3	walktrap_log_gic_4	louvain_log_gic_4	leiden_log_gic_4	walktrap_log_ebic	louvain_log_ebic	leiden_log_ebic
balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor	.21	.19	.18	.21	.18	.18	.20	.18	.17	.16	.15	.14
fct	.05	.02	.02	.04	.02	.02	.04	.02	.02	.04	.02	.02
items	.00	.00	.00	.00	.00	.00	.01	.00	.00	.00	.00	.00
linear	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
loading	.44	.45	.43	.46	.45	.45	.56	.56	.56	.69	.70	.70
responses	.21	.20	.19	.19	.17	.16	.09	.09	.08	.03	.04	.03
sample	.32	.34	.33	.31	.33	.32	.33	.35	.34	.38	.40	.40
f_cor:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:linear	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:loading	.11	.10	.10	.10	.09	.09	.09	.08	.08	.05	.04	.05
f_cor:responses	.01	.01	.01	.01	.01	.01	.02	.02	.02	.02	.02	.02
f_cor:sample	.00	.01	.01	.00	.01	.01	.00	.00	.01	.00	.00	.00
fct:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor	.02	.01	.01	.02	.01	.01	.01	.01	.01	.01	.01	.01
fct:items	.00	.00	.00	.00	.01	.01	.00	.01	.01	.00	.00	.00
fct:linear	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:loading	.00	.00	.00	.01	.01	.01	.03	.02	.02	.02	.02	.02
fct:responses	.01	.01	.01	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:sample	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
linear:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
linear:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
linear:loading	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
loading:items	.02	.01	.01	.01	.01	.01	.00	.00	.00	.00	.00	.00
responses:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:items	.01	.01	.01	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:linear	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:loading	.00	.00	.00	.00	.00	.00	.00	.00	.00	.01	.01	.01
responses:sample	.08	.07	.07	.06	.05	.05	.01	.01	.01	.00	.00	.00
sample:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:items	.01	.01	.01	.01	.01	.01	.00	.00	.00	.00	.01	.00
sample:linear	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:loading	.07	.09	.10	.09	.12	.12	.20	.22	.24	.31	.32	.33
f_cor:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:linear:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00

f_cor:linear:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:linear:loading	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:loading:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:responses:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:responses:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:responses:linear	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:responses:loading	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:responses:sample	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:sample:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:sample:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:sample:linear	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:sample:loading	.02	.02	.01	.02	.02	.02	.04	.03	.03	.07	.07	.07
fct:f_cor:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:linear	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:loading	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:responses	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:sample	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:linear:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:linear:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:linear:loading	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:loading:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:linear	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:loading	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:sample	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:sample:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:sample:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:sample:linear	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:sample:loading	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
linear:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
linear:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
linear:loading:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:linear:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:linear:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:linear:loading	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:loading:items	.01	.01	.01	.01	.01	.01	.00	.00	.00	.00	.00	.00
responses:sample:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:items	.01	.01	.01	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:linear	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:loading	.05	.05	.04	.05	.05	.04	.03	.03	.03	.03	.03	.03
sample:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:linear:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:linear:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:linear:loading	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:loading:items	.00	.00	.00	.00	.00	.00	.01	.00	.00	.01	.00	.00
f_cor:linear:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:linear:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:linear:loading:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00

f_cor:responses:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:responses:linear:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:responses:linear:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:responses:linear:loading	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:responses:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:responses:loading:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:responses:sample:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:responses:sample:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:responses:sample:linear	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:responses:sample:loading	.01	.01	.01	.00	.01	.01	.00	.01	.01	.00	.01	.01
f_cor:sample:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:sample:linear:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:sample:linear:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:sample:linear:loading	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:sample:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:sample:loading:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:linear:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:linear:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:linear:loading	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:loading:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:responses:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:responses:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:responses:linear	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:responses:loading	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:responses:sample	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:sample:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:sample:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:sample:linear	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:sample:loading	.00	.00	.00	.00	.00	.00	.01	.00	.00	.00	.00	.00
fct:linear:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:linear:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:linear:loading:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:linear:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:linear:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:linear:loading	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:loading:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:sample:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:sample:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:sample:linear	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:sample:loading	.00	.00	.00	.01	.00	.00	.00	.00	.00	.00	.00	.00
fct:sample:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:sample:linear:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:sample:linear:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:sample:linear:loading	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:sample:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:sample:loading:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
linear:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:linear:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:linear:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:linear:loading:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:linear:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00

responses:sample:linear:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:linear:loading	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:loading:items	.01	.01	.01	.01	.01	.01	.00	.00	.00	.00	.00	.00
sample:linear:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:linear:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:linear:loading:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:linear:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:responses:linear:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:responses:linear:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:responses:linear:loading:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:responses:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:responses:sample:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:responses:sample:linear:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:responses:sample:linear:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:responses:sample:linear:loading	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:responses:sample:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:responses:sample:loading:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:sample:linear:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:sample:linear:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:sample:linear:loading:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:sample:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:linear:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:linear:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:linear:loading:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:responses:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:responses:linear:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:responses:linear:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:responses:linear:loading	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:responses:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:responses:loading:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:responses:sample:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:responses:sample:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:responses:sample:linear	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:responses:sample:loading	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:sample:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:sample:linear:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:sample:linear:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:sample:linear:loading	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:sample:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:sample:loading:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:linear:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:linear:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:linear:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:linear:loading:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:sample:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:sample:linear:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:sample:linear:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:sample:linear:loading	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:sample:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:sample:loading:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:sample:linear:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:sample:linear:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:sample:linear:loading:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:sample:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00

responses:linear:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:linear:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:linear:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:linear:loading:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:linear:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:responses:linear:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:responses:sample:linear:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:responses:sample:linear:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:responses:sample:linear:loading:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:responses:sample:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:sample:linear:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:linear:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:responses:linear:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:responses:linear:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:responses:linear:loading:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:responses:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:responses:sample:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:responses:sample:linear:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:responses:sample:linear:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:responses:sample:linear:loading	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:responses:sample:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:responses:sample:loading:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:sample:linear:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:sample:linear:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:sample:linear:loading:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:sample:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:linear:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:sample:linear:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:sample:linear:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:sample:linear:loading:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:sample:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:sample:linear:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:linear:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:responses:sample:linear:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:responses:linear:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:responses:sample:linear:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:responses:sample:linear:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:responses:sample:linear:loading:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:responses:sample:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:sample:linear:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:sample:linear:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:responses:sample:linear:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00

Table 37. ARI Partial Eta Squared by Term Interaction (Part 5)

Term	R2Z_walktrap	R2Z_louvain	R2Z_leiden	fspe_none	fspe_geominQ	fspe_varimax	fspe_oblimin	EGAnet	PA_FA_none	PA_FA_geomi	PA_FA_varim	PA_FA_oblim	PA_PC_none	PA_PC_geomi	PA_PC_varim	PA_PC_oblim
balance	.00	.00	.00	.06	.00	.00	.00	.00	.09	.01	.01	.01	.06	.00	.00	.00
f_cor	.22	.18	.18	.70	.33	.31	.32	.25	.69	.17	.16	.16	.72	.49	.49	.49
fct	.20	.11	.11	.05	.03	.03	.03	.01	.02	.00	.00	.00	.05	.02	.02	.02
items	.00	.02	.01	.00	.09	.08	.09	.05	.01	.14	.13	.12	.00	.16	.16	.16
linear	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00

loading	.56	.52	.52	.02	.53	.53	.53	.45	.04	.60	.59	.61	.01	.26	.26	.27
responses	.09	.09	.09	.00	.10	.10	.10	.04	.00	.13	.14	.17	.00	.01	.00	.01
sample	.44	.42	.41	.01	.20	.20	.20	.17	.00	.13	.13	.13	.01	.12	.12	.12
f_cor:balance	.00	.00	.00	.02	.00	.00	.00	.00	.04	.00	.00	.00	.03	.00	.00	.00
f_cor:items	.00	.00	.00	.01	.01	.01	.01	.03	.03	.00	.00	.00	.00	.10	.10	.10
f_cor:linear	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:loading	.03	.05	.05	.03	.21	.20	.21	.08	.09	.08	.07	.07	.03	.05	.04	.04
f_cor:responses	.00	.01	.01	.00	.02	.02	.02	.01	.00	.01	.01	.01	.00	.01	.01	.01
f_cor:sample	.00	.01	.01	.02	.02	.02	.02	.00	.01	.05	.05	.04	.02	.02	.02	.02
fct:balance	.00	.00	.00	.00	.00	.00	.00	.00	.01	.00	.00	.00	.00	.00	.00	.00
fct:f_cor	.01	.01	.01	.02	.01	.01	.01	.00	.00	.03	.03	.03	.02	.01	.01	.01
fct:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.01	.01	.01	.00	.00	.00	.00
fct:linear	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:loading	.02	.01	.02	.00	.02	.02	.02	.02	.00	.01	.01	.01	.00	.00	.00	.00
fct:responses	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:sample	.02	.02	.02	.00	.00	.00	.00	.00	.00	.01	.01	.01	.00	.00	.00	.00
items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
linear:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
linear:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
linear:loading	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.01	.01	.01	.00	.00	.00	.00
loading:items	.00	.00	.00	.00	.05	.05	.05	.00	.01	.11	.12	.11	.00	.00	.00	.00
responses:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.01	.02	.02	.00	.00	.00	.00
responses:linear	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:loading	.01	.02	.02	.00	.04	.04	.04	.02	.00	.06	.06	.07	.00	.01	.01	.02
responses:sample	.00	.01	.01	.00	.01	.00	.01	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:items	.03	.04	.04	.00	.01	.01	.01	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:linear	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:loading	.05	.12	.13	.01	.12	.12	.11	.14	.00	.05	.05	.04	.00	.03	.03	.03
f_cor:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:linear:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:linear:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:linear:loading	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:loading:items	.00	.00	.00	.00	.01	.01	.01	.01	.02	.02	.02	.02	.00	.02	.02	.02
f_cor:responses:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:responses:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:responses:linear	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:responses:loading	.01	.00	.00	.00	.01	.01	.01	.00	.00	.01	.01	.01	.00	.00	.00	.01
f_cor:responses:sample	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:sample:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:sample:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.01	.01	.01
f_cor:sample:linear	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:sample:loading	.05	.03	.03	.01	.02	.02	.02	.02	.00	.01	.01	.01	.00	.01	.01	.01
fct:f_cor:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.01	.01	.01	.00	.00	.00	.00
fct:f_cor:linear	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:loading	.01	.00	.00	.00	.00	.00	.00	.01	.01	.01	.01	.01	.00	.00	.00	.00
fct:f_cor:responses	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:sample	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:linear:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:linear:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:linear:loading	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:loading:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.02	.02	.02	.00	.00	.00	.00

fct:responses:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:linear	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:loading	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:sample	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:sample:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:sample:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:sample:linear	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:sample:loading	.04	.01	.01	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
linear:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
linear:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
linear:loading:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:linear:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:linear:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:linear:loading	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:loading:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.03	.02	.03	.00	.01	.00	.01
responses:sample:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:linear	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:loading	.02	.01	.01	.00	.01	.01	.01	.01	.00	.01	.01	.02	.00	.00	.00	.00
sample:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:linear:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:linear:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:linear:loading	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:loading:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.01	.01	.01	.00	.00	.00	.00
f_cor:linear:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:linear:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:linear:loading:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:responses:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:responses:linear:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:responses:linear:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:responses:linear:loading	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:responses:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:responses:loading:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:responses:sample:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:responses:sample:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:responses:sample:linear	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:responses:sample:loading	.00	.01	.01	.00	.03	.03	.03	.01	.00	.02	.02	.02	.00	.00	.00	.00
f_cor:sample:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:sample:linear:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:sample:linear:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:sample:linear:loading	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:sample:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:sample:loading:items	.00	.00	.00	.00	.02	.02	.02	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:linear:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:linear:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:linear:loading	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:loading:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:responses:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:responses:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:responses:linear	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00

fct:f_cor:responses:loading	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:responses:sample	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:sample:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:sample:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:sample:linear	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:sample:loading	.01	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:linear:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:linear:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:linear:loading:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:linear:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
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fct:responses:linear:loading	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
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fct:responses:sample:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:sample:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:sample:linear	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:sample:loading	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:sample:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:sample:linear:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:sample:linear:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:sample:linear:loading	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:sample:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:sample:loading:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
linear:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:linear:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:linear:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:linear:loading:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:linear:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:linear:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:linear:loading	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:loading:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:linear:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:linear:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:linear:loading:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:linear:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:responses:linear:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:responses:linear:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:responses:linear:loading:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:responses:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:responses:sample:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:responses:sample:linear:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:responses:sample:linear:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
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f_cor:responses:sample:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:responses:sample:loading:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:sample:linear:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:sample:linear:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:sample:linear:loading:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:sample:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:linear:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:linear:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00

fct:f_cor:linear:loading:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:responses:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:responses:linear:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:responses:linear:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:responses:linear:loading	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:responses:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
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fct:f_cor:responses:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
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fct:f_cor:responses:sample:linear:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:responses:sample:linear:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:responses:sample:linear:loading	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:responses:sample:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:responses:sample:loading:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:sample:linear:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:sample:linear:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00

fct:f_cor:sample:linear:loading:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:sample:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:linear:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:sample:linear:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:sample:linear:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:sample:linear:loading:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:sample:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:sample:linear:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:linear:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor:responses:sample:linear:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:responses:linear:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:responses:sample:linear:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:responses:sample:linear:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:responses:sample:linear:loading:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:responses:sample:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:sample:linear:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:sample:linear:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor:responses:sample:linear:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00

Table 38. ARI Partial Eta Squared by Term Interaction (Part 1)

Term	**walktrap_atan_bic**	**louvain_atan_bic**	**leiden_atan_bic**	**walktrap_atan_gic_3**	**louvain_atan_gic_3**	**leiden_atan_gic_3**	**walktrap_atan_gic_4**	**louvain_atan_gic_4**	**leiden_atan_gic_4**	**walktrap_atan_ebic**	**louvain_atan_ebic**	**leiden_atan_ebic**
balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor	.09	.08	.07	.10	.07	.07	.09	.06	.05	.07	.04	.03
fct	.10	.04	.04	.10	.03	.03	.07	.03	.03	.05	.02	.01
items	.01	.01	.01	.01	.01	.01	.02	.02	.02	.04	.02	.02
linear	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
loading	.26	.27	.26	.28	.27	.26	.35	.32	.32	.39	.39	.39
responses	.10	.08	.08	.08	.07	.07	.04	.04	.03	.03	.03	.02
sample	.22	.22	.22	.22	.22	.22	.23	.23	.23	.21	.20	.20
balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:balance	.00	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01
fct:f_cor	.03	.01	.01	.03	.01	.01	.02	.00	.00	.01	.00	.00
fct:items	.01	.09	.08	.01	.07	.07	.01	.05	.06	.01	.03	.03
fct:linear	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:loading	.01	.01	.01	.01	.00	.00	.03	.01	.01	.04	.01	.01
fct:responses	.03	.01	.01	.01	.01	.00	.00	.01	.01	.00	.00	.00
fct:sample	.01	.02	.01	.01	.01	.01	.01	.01	.01	.00	.00	.00
items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
linear:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
linear:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
linear:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
linear:loading	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
loading:balance	.00	.00	.00	.00	.00	.00	.01	.01	.01	.01	.01	.01
loading:f_cor	.03	.02	.02	.03	.02	.01	.02	.01	.01	.01	.01	.01
loading:items	.01	.00	.00	.02	.02	.01	.04	.03	.03	.04	.02	.02
responses:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:items	.00	.01	.01	.00	.01	.01	.00	.01	.00	.00	.00	.00

responses:linear	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:loading	.01	.01	.01	.01	.00	.01	.00	.00	.00	.00	.00	.00
responses:sample	.02	.02	.02	.02	.01	.01	.01	.00	.00	.00	.01	.00
sample:balance	.00	.00	.00	.00	.00	.00	.01	.01	.01	.00	.00	.00
sample:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:items	.03	.03	.04	.05	.06	.05	.07	.07	.07	.05	.04	.04
sample:linear	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:loading	.05	.05	.05	.07	.06	.06	.11	.10	.10	.12	.12	.12
fct:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:items:f_cor	.01	.03	.03	.01	.02	.02	.01	.02	.02	.00	.01	.01
fct:linear:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:linear:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:linear:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:linear:loading	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:loading:balance	.00	.01	.00	.01	.01	.01	.02	.01	.01	.01	.01	.01
fct:loading:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.01	.00	.01	.01
fct:loading:items	.01	.03	.03	.00	.01	.01	.01	.01	.01	.01	.01	.01
fct:responses:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:items	.00	.01	.01	.00	.01	.01	.00	.01	.01	.00	.00	.01
fct:responses:linear	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:loading	.01	.02	.02	.01	.01	.01	.01	.01	.01	.00	.00	.00
fct:responses:sample	.00	.01	.00	.00	.01	.00	.00	.01	.01	.00	.01	.01
fct:sample:balance	.00	.00	.00	.00	.00	.01	.01	.01	.01	.00	.00	.00
fct:sample:f_cor	.00	.00	.00	.00	.00	.00	.00	.01	.01	.00	.01	.01
fct:sample:items	.00	.02	.01	.00	.01	.01	.00	.00	.00	.00	.01	.01
fct:sample:linear	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:sample:loading	.02	.03	.02	.01	.01	.02	.00	.01	.01	.01	.01	.01
items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
linear:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
linear:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
linear:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
linear:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
linear:loading:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
linear:loading:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
loading:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
loading:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.01	.00	.00
responses:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:linear:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:linear:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:linear:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:linear:loading	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:loading:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:loading:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:f_cor	.01	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:items	.00	.00	.01	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:linear	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:loading	.06	.05	.04	.04	.04	.04	.03	.03	.03	.01	.01	.01
sample:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:items:f_cor	.00	.00	.00	.00	.00	.00	.01	.00	.00	.01	.00	.00
sample:linear:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00

sample:linear:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:linear:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:linear:loading	.00	.01	.01	.00	.01	.01	.00	.00	.00	.00	.00	.00
sample:loading:balance	.00	.00	.00	.00	.00	.00	.01	.01	.01	.00	.01	.01
sample:loading:f_cor	.02	.03	.03	.02	.03	.03	.03	.05	.04	.03	.04	.05
sample:loading:items	.02	.02	.02	.05	.04	.03	.06	.04	.04	.03	.02	.02
fct:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:linear:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:linear:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:linear:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:linear:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.01	.01
fct:linear:loading:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:linear:loading:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:loading:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:loading:items:f_cor	.00	.00	.01	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:linear:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:linear:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:linear:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:linear:loading	.01	.00	.00	.01	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:loading:balance	.00	.01	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:loading:f_cor	.01	.00	.00	.01	.00	.01	.00	.00	.00	.00	.00	.00
fct:responses:loading:items	.01	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:sample:balance	.01	.00	.00	.01	.00	.00	.00	.00	.00	.01	.01	.01
fct:responses:sample:f_cor	.00	.01	.00	.00	.01	.01	.00	.01	.01	.00	.00	.00
fct:responses:sample:items	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01
fct:responses:sample:linear	.00	.00	.00	.00	.01	.01	.00	.00	.00	.00	.00	.00
fct:responses:sample:loading	.02	.01	.02	.02	.02	.01	.01	.01	.01	.01	.01	.02
fct:sample:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:sample:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:sample:items:f_cor	.01	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:sample:linear:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:sample:linear:f_cor	.00	.00	.00	.00	.01	.00	.00	.00	.00	.00	.00	.00
fct:sample:linear:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:sample:linear:loading	.01	.01	.01	.01	.01	.01	.01	.00	.00	.00	.00	.00
fct:sample:loading:balance	.00	.01	.01	.00	.01	.01	.01	.01	.01	.00	.00	.00
fct:sample:loading:f_cor	.01	.01	.01	.01	.01	.01	.02	.01	.02	.01	.01	.01
fct:sample:loading:items	.01	.01	.01	.01	.01	.01	.02	.01	.02	.01	.01	.01
linear:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
linear:loading:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
linear:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
linear:loading:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
loading:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:linear:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:linear:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:linear:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:linear:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:linear:loading:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:linear:loading:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:loading:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:loading:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00

responses:sample:items:f_cor	.01	.01	.00	.00	.00	.00	.00	.00	.00	.00	.01	.00
responses:sample:linear:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:linear:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:linear:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:linear:loading	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:loading:balance	.00	.01	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:loading:f_cor	.01	.00	.01	.00	.01	.01	.01	.01	.01	.01	.01	.01
responses:sample:loading:items	.01	.01	.00	.00	.01	.01	.00	.00	.00	.02	.01	.01
sample:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:linear:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:linear:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:linear:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:linear:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:linear:loading:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:linear:loading:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:loading:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:loading:items:f_cor	.01	.01	.01	.01	.01	.00	.00	.01	.00	.00	.00	.00
fct:linear:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:linear:loading:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:linear:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:linear:loading:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:loading:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:linear:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:linear:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:linear:items:f_cor	.00	.00	.00	.00	.00	.00	.01	.00	.00	.00	.00	.00
fct:responses:linear:loading:balance	.00	.00	.00	.00	.01	.00	.00	.00	.00	.00	.00	.00
fct:responses:linear:loading:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.01	.00	.01	.01
fct:responses:linear:loading:items	.00	.01	.00	.00	.00	.00	.01	.00	.01	.00	.00	.00
fct:responses:loading:balance:f_cor	.00	.00	.00	.01	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:loading:items:balance	.00	.00	.00	.00	.00	.00	.01	.00	.00	.01	.00	.00
fct:responses:loading:items:f_cor	.01	.00	.00	.01	.00	.00	.01	.01	.01	.01	.01	.01
fct:responses:sample:balance:f_cor	.00	.00	.00	.00	.00	.00	.01	.01	.00	.01	.00	.00
fct:responses:sample:items:balance	.00	.00	.01	.00	.00	.00	.01	.00	.00	.00	.00	.00
fct:responses:sample:items:f_cor	.00	.00	.01	.01	.01	.01	.00	.01	.00	.01	.01	.01
fct:responses:sample:linear:balance	.00	.01	.01	.00	.01	.01	.00	.01	.01	.01	.00	.01
fct:responses:sample:linear:f_cor	.00	.00	.01	.00	.01	.01	.01	.01	.00	.00	.00	.00
fct:responses:sample:linear:items	.00	.01	.01	.00	.00	.00	.01	.00	.00	.00	.01	.00
fct:responses:sample:linear:loading	.01	.01	.00	.01	.01	.01	.01	.01	.00	.01	.01	.01
fct:responses:sample:loading:balance	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01
fct:responses:sample:loading:f_cor	.01	.01	.02	.01	.01	.01	.01	.01	.01	.01	.01	.01
fct:responses:sample:loading:items	.01	.01	.01	.01	.01	.01	.02	.02	.02	.02	.01	.01
fct:sample:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:sample:linear:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:sample:linear:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:sample:linear:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:sample:linear:loading:balance	.01	.01	.00	.01	.01	.01	.00	.01	.01	.01	.01	.01
fct:sample:linear:loading:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:sample:linear:loading:items	.00	.00	.00	.00	.01	.00	.01	.01	.01	.00	.01	.01
fct:sample:loading:balance:f_cor	.00	.01	.01	.00	.00	.00	.01	.01	.01	.01	.00	.00
fct:sample:loading:items:balance	.00	.00	.00	.00	.01	.00	.01	.01	.00	.00	.01	.01
fct:sample:loading:items:f_cor	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01
linear:loading:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:linear:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:linear:loading:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:linear:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:linear:loading:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00

responses:loading:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:linear:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:linear:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:linear:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:linear:loading:balance	.00	.01	.00	.00	.00	.00	.00	.00	.00	.00	.00	.01
responses:sample:linear:loading:f_cor	.00	.00	.00	.00	.00	.00	.01	.01	.00	.00	.01	.00
responses:sample:linear:loading:items	.00	.01	.00	.00	.00	.00	.01	.00	.00	.00	.00	.00
responses:sample:loading:balance:f_cor	.00	.01	.01	.00	.01	.00	.00	.00	.00	.00	.00	.00
responses:sample:loading:items:balance	.01	.00	.00	.00	.00	.00	.01	.00	.00	.00	.00	.00
responses:sample:loading:items:f_cor	.00	.00	.00	.00	.00	.00	.01	.01	.01	.01	.01	.01
sample:linear:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:linear:loading:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:linear:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:linear:loading:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:loading:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:linear:loading:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:linear:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:linear:loading:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:linear:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:linear:loading:items:f_cor	.00	.00	.00	.01	.01	.00	.01	.01	.01	.00	.01	.00
fct:responses:loading:items:balance:f_cor	.01	.00	.00	.01	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:sample:items:balance:f_cor	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01	.00	.01
fct:responses:sample:linear:balance:f_cor	.01	.01	.01	.01	.01	.01	.01	.01	.01	.00	.00	.01
fct:responses:sample:linear:items:balance	.01	.00	.00	.01	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:sample:linear:items:f_cor	.01	.00	.00	.00	.01	.00	.01	.01	.01	.01	.01	.01
fct:responses:sample:linear:loading:balance	.01	.01	.01	.02	.01	.01	.01	.01	.01	.02	.01	.01
fct:responses:sample:linear:loading:f_cor	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01
fct:responses:sample:linear:loading:items	.01	.02	.01	.00	.01	.01	.01	.01	.01	.01	.01	.01
fct:responses:sample:loading:balance:f_cor	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01
fct:responses:sample:loading:items:balance	.01	.01	.01	.01	.01	.01	.01	.00	.01	.01	.01	.01
fct:responses:sample:loading:items:f_cor	.01	.01	.01	.01	.01	.01	.02	.02	.02	.02	.02	.02
fct:sample:linear:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:sample:linear:loading:balance:f_cor	.00	.01	.01	.01	.01	.00	.00	.00	.00	.00	.00	.00
fct:sample:linear:loading:items:balance	.00	.00	.01	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:sample:linear:loading:items:f_cor	.01	.01	.00	.00	.00	.00	.00	.01	.00	.00	.00	.00
fct:sample:loading:items:balance:f_cor	.00	.01	.01	.00	.00	.00	.00	.01	.01	.00	.00	.00
responses:linear:loading:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:linear:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:linear:loading:balance:f_cor	.00	.01	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:linear:loading:items:balance	.00	.00	.00	.00	.01	.00	.00	.01	.01	.00	.00	.00
responses:sample:linear:loading:items:f_cor	.00	.00	.01	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:loading:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:linear:loading:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:linear:loading:items:balance:f_cor	.01	.01	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:sample:linear:items:balance:f_cor	.00	.00	.01	.00	.01	.01	.00	.00	.00	.00	.01	.01
fct:responses:sample:linear:loading:balance:f_cor	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01
fct:responses:sample:linear:loading:items:balance	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01	.00	.00
fct:responses:sample:linear:loading:items:f_cor	.01	.01	.01	.01	.01	.01	.02	.02	.02	.02	.01	.02
fct:responses:sample:loading:items:balance:f_cor	.02	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01
fct:sample:linear:loading:items:balance:f_cor	.01	.00	.01	.00	.00	.00	.01	.00	.00	.00	.00	.00
responses:sample:linear:loading:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.01	.00
fct:responses:sample:linear:loading:items:balance:f_cor	.01	.01	.01	.01	.01	.01	.01	.00	.01	.00	.01	.01

Table 39. MAE Partial Eta Squared by Term Interaction (Part 2)

Term	walktrap_lasso_bic	louvain_lasso_bic	leiden_lasso_bic	walktrap_lasso_gic_3	louvain_lasso_gic_3	leiden_lasso_gic_3	walktrap_lasso_gic_4	louvain_lasso_gic_4	leiden_lasso_gic_4	walktrap_lasso_ebic	louvain_lasso_ebic	leiden_lasso_ebic
balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor	.16	.08	.08	.16	.08	.07	.16	.09	.08	.10	.06	.06
fct	.28	.13	.14	.27	.14	.14	.22	.15	.15	.21	.18	.18
items	.02	.00	.01	.03	.00	.00	.02	.00	.00	.00	.00	.00
linear	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
loading	.19	.21	.21	.22	.25	.24	.32	.32	.32	.45	.44	.45
responses	.21	.14	.12	.19	.12	.11	.04	.02	.02	.00	.00	.00
sample	.18	.20	.20	.16	.22	.23	.22	.27	.27	.30	.32	.32
balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor	.07	.02	.02	.08	.03	.03	.08	.04	.04	.06	.03	.03
fct:items	.02	.08	.09	.04	.09	.09	.03	.05	.04	.01	.01	.01
fct:linear	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:loading	.03	.01	.02	.05	.03	.03	.09	.08	.08	.12	.11	.11
fct:responses	.10	.02	.02	.06	.01	.01	.00	.02	.02	.00	.01	.01
fct:sample	.03	.01	.01	.03	.02	.02	.05	.05	.05	.06	.07	.07
items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
items:f_cor	.02	.01	.01	.03	.01	.01	.02	.00	.00	.02	.01	.01
linear:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
linear:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
linear:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
linear:loading	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
loading:f_cor	.05	.03	.03	.05	.03	.03	.05	.03	.03	.03	.02	.02
loading:items	.01	.00	.01	.01	.01	.01	.00	.00	.00	.00	.00	.00
responses:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:f_cor	.01	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:items	.00	.01	.01	.00	.01	.01	.00	.00	.00	.00	.00	.00
responses:linear	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:loading	.02	.01	.01	.02	.01	.01	.01	.01	.02	.02	.02	.02
responses:sample	.07	.05	.05	.05	.04	.03	.00	.00	.00	.01	.01	.01
sample:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:f_cor	.01	.00	.00	.01	.00	.00	.00	.00	.00	.00	.01	.01
sample:items	.01	.01	.01	.01	.02	.02	.00	.01	.01	.00	.00	.00
sample:linear	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:loading	.01	.04	.04	.01	.07	.07	.07	.15	.15	.19	.23	.23
fct:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:items:balance	.00	.00	.00	.01	.00	.01	.00	.00	.00	.00	.00	.00
fct:items:f_cor	.02	.02	.02	.02	.02	.02	.01	.01	.01	.01	.00	.00
fct:linear:balance	.00	.00	.00	.00	.00	.00	.01	.00	.00	.00	.00	.00
fct:linear:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:linear:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:linear:loading	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:loading:f_cor	.02	.00	.00	.03	.01	.01	.03	.01	.01	.01	.01	.01
fct:loading:items	.01	.02	.02	.01	.01	.02	.00	.01	.00	.00	.00	.00
fct:responses:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:f_cor	.01	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:items	.00	.02	.02	.00	.02	.02	.00	.01	.01	.00	.00	.00
fct:responses:linear	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00

fct:responses:loading	.03	.02	.03	.03	.03	.03	.02	.03	.03	.01	.01	.01
fct:responses:sample	.02	.01	.01	.01	.01	.01	.01	.02	.02	.01	.02	.02
fct:sample:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:sample:f_cor	.01	.00	.00	.00	.00	.00	.00	.01	.01	.00	.01	.00
fct:sample:items	.00	.01	.01	.00	.01	.01	.00	.00	.00	.00	.00	.00
fct:sample:linear	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:sample:loading	.02	.01	.01	.01	.01	.01	.01	.02	.02	.03	.05	.05
items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
linear:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
linear:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
linear:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
linear:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
linear:loading:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
linear:loading:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
loading:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
loading:items:f_cor	.00	.00	.00	.01	.00	.00	.00	.00	.00	.00	.00	.00
responses:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:linear:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:linear:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:linear:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:linear:loading	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:loading:balance	.00	.00	.00	.01	.01	.01	.01	.01	.01	.00	.00	.00
responses:loading:f_cor	.00	.00	.00	.01	.00	.00	.00	.00	.00	.01	.00	.00
responses:loading:items	.00	.00	.00	.00	.00	.00	.01	.01	.01	.00	.00	.00
responses:sample:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:f_cor	.01	.00	.00	.01	.00	.00	.01	.00	.00	.00	.00	.00
responses:sample:items	.01	.01	.01	.00	.01	.01	.00	.00	.01	.00	.00	.00
responses:sample:linear	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:loading	.05	.05	.05	.06	.04	.05	.07	.06	.06	.03	.02	.02
sample:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:linear:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:linear:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:linear:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:linear:loading	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:loading:balance	.01	.00	.01	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:loading:f_cor	.04	.01	.01	.04	.01	.01	.03	.01	.01	.02	.01	.01
sample:loading:items	.02	.02	.02	.03	.03	.03	.02	.02	.01	.02	.02	.02
fct:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:linear:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:linear:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:linear:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:linear:loading:balance	.00	.00	.00	.00	.00	.00	.01	.01	.01	.01	.01	.01
fct:linear:loading:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:linear:loading:items	.01	.00	.00	.01	.00	.01	.00	.00	.00	.00	.00	.00
fct:loading:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:loading:items:f_cor	.00	.00	.00	.00	.00	.01	.00	.00	.00	.01	.01	.00
fct:responses:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.01	.01	.01
fct:responses:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:linear:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:linear:f_cor	.00	.00	.00	.00	.00	.00	.00	.01	.01	.00	.00	.00
fct:responses:linear:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00

fct:responses:linear:loading	.00	.00	.00	.01	.00	.01	.00	.00	.00	.00	.00	.00
fct:responses:loading:balance	.00	.00	.00	.01	.01	.00	.00	.00	.00	.00	.00	.00
fct:responses:loading:f_cor	.00	.00	.00	.01	.00	.00	.00	.00	.00	.00	.01	.00
fct:responses:loading:items	.01	.00	.00	.00	.01	.00	.00	.00	.00	.00	.01	.01
fct:responses:sample:balance	.00	.00	.01	.01	.00	.00	.01	.01	.01	.00	.00	.00
fct:responses:sample:f_cor	.00	.00	.01	.00	.01	.00	.00	.00	.00	.00	.00	.00
fct:responses:sample:items	.01	.01	.01	.01	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:sample:linear	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:sample:loading	.03	.02	.02	.03	.03	.03	.04	.03	.03	.02	.02	.02
fct:sample:balance:f_cor	.01	.01	.01	.00	.01	.01	.00	.00	.00	.00	.00	.00
fct:sample:items:balance	.00	.00	.00	.01	.01	.00	.00	.00	.00	.00	.00	.00
fct:sample:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.01	.01	.00	.00	.00
fct:sample:linear:balance	.00	.00	.00	.00	.00	.00	.01	.01	.01	.00	.00	.00
fct:sample:linear:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:sample:linear:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:sample:linear:loading	.00	.01	.01	.00	.01	.01	.01	.01	.01	.01	.01	.01
fct:sample:loading:balance	.00	.00	.01	.00	.00	.01	.00	.00	.00	.00	.01	.00
fct:sample:loading:f_cor	.02	.01	.01	.01	.01	.01	.01	.01	.00	.01	.00	.01
fct:sample:loading:items	.01	.01	.01	.01	.01	.02	.01	.01	.01	.02	.02	.02
linear:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
linear:loading:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
linear:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
linear:loading:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
loading:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:linear:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:linear:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:linear:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:linear:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:linear:loading:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:linear:loading:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:loading:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:loading:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:linear:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:linear:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:linear:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:linear:loading	.00	.00	.00	.01	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:loading:balance	.01	.00	.00	.01	.01	.01	.01	.01	.01	.00	.00	.00
responses:sample:loading:f_cor	.01	.00	.00	.01	.01	.01	.00	.01	.01	.01	.00	.00
responses:sample:loading:items	.00	.01	.00	.01	.01	.01	.01	.01	.01	.01	.00	.00
sample:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:linear:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:linear:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:linear:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:linear:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:linear:loading:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:linear:loading:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:loading:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:loading:items:f_cor	.01	.00	.00	.01	.00	.00	.01	.01	.01	.00	.00	.00
fct:linear:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:linear:loading:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:linear:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:linear:loading:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00

fct:loading:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:linear:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:linear:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:linear:items:f_cor	.01	.00	.00	.01	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:linear:loading:balance	.00	.00	.00	.00	.01	.00	.00	.00	.00	.00	.00	.00
fct:responses:linear:loading:f_cor	.00	.00	.01	.00	.00	.01	.01	.01	.01	.00	.00	.01
fct:responses:linear:loading:items	.00	.00	.00	.00	.01	.00	.01	.01	.01	.00	.00	.00
fct:responses:loading:balance:f_cor	.00	.00	.00	.00	.00	.00	.01	.00	.00	.01	.01	.01
fct:responses:loading:items:balance	.00	.01	.01	.01	.01	.01	.00	.00	.00	.00	.00	.00
fct:responses:loading:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:sample:balance:f_cor	.00	.00	.00	.00	.00	.00	.01	.01	.00	.01	.01	.01
fct:responses:sample:items:balance	.01	.01	.00	.01	.01	.01	.01	.00	.01	.01	.00	.00
fct:responses:sample:items:f_cor	.01	.00	.01	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:sample:linear:balance	.00	.01	.01	.00	.01	.01	.01	.01	.01	.00	.01	.01
fct:responses:sample:linear:f_cor	.00	.00	.00	.01	.01	.00	.00	.00	.00	.01	.01	.01
fct:responses:sample:linear:items	.00	.01	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:sample:linear:loading	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01
fct:responses:sample:loading:balance	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01
fct:responses:sample:loading:f_cor	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01	.02	.02
fct:responses:sample:loading:items	.01	.01	.02	.02	.02	.02	.01	.02	.02	.01	.01	.01
fct:sample:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:sample:linear:balance:f_cor	.00	.00	.01	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:sample:linear:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:sample:linear:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:sample:linear:loading:balance	.00	.00	.01	.00	.01	.01	.01	.02	.01	.00	.00	.01
fct:sample:linear:loading:f_cor	.01	.00	.01	.00	.00	.00	.00	.00	.00	.01	.01	.01
fct:sample:linear:loading:items	.00	.01	.01	.01	.01	.01	.00	.01	.01	.00	.01	.01
fct:sample:loading:balance:f_cor	.01	.01	.01	.01	.01	.00	.01	.01	.00	.00	.00	.00
fct:sample:loading:items:balance	.00	.00	.01	.01	.01	.01	.00	.00	.00	.00	.00	.00
fct:sample:loading:items:f_cor	.00	.00	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01
linear:loading:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:linear:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:linear:loading:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:linear:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:linear:loading:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:loading:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:linear:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:linear:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:linear:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:linear:loading:balance	.00	.00	.00	.00	.00	.00	.00	.01	.01	.00	.00	.00
responses:sample:linear:loading:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:linear:loading:items	.01	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:loading:balance:f_cor	.00	.01	.01	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.01	.00	.00	.00
responses:sample:loading:items:f_cor	.00	.00	.00	.00	.01	.01	.01	.01	.01	.01	.01	.01
sample:linear:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:linear:loading:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:linear:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:linear:loading:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:loading:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:linear:loading:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:linear:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:linear:loading:balance:f_cor	.00	.00	.00	.01	.00	.01	.00	.00	.00	.00	.00	.00
fct:responses:linear:loading:items:balance	.00	.00	.00	.00	.00	.00	.01	.01	.01	.00	.00	.00
fct:responses:linear:loading:items:f_cor	.01	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:loading:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00

fct:responses:sample:items:balance:f_cor	.00	.00	.01	.00	.00	.00	.01	.01	.01	.01	.01	.01
fct:responses:sample:linear:balance:f_cor	.01	.01	.01	.00	.00	.00	.01	.01	.01	.00	.01	.01
fct:responses:sample:linear:items:balance	.00	.00	.00	.01	.00	.01	.00	.00	.00	.01	.01	.01
fct:responses:sample:linear:items:f_cor	.01	.01	.01	.00	.01	.01	.00	.00	.00	.01	.01	.01
fct:responses:sample:linear:loading:balance	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01	.02	.01
fct:responses:sample:linear:loading:f_cor	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01
fct:responses:sample:linear:loading:items	.02	.01	.01	.01	.01	.01	.01	.01	.01	.01	.00	.00
fct:responses:sample:loading:balance:f_cor	.00	.01	.01	.00	.01	.01	.01	.01	.01	.01	.01	.01
fct:responses:sample:loading:items:balance	.01	.01	.02	.01	.02	.02	.01	.01	.01	.01	.01	.01
fct:responses:sample:loading:items:f_cor	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01
fct:sample:linear:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:sample:linear:loading:balance:f_cor	.01	.01	.01	.01	.00	.01	.01	.00	.00	.00	.00	.00
fct:sample:linear:loading:items:balance	.00	.00	.00	.00	.00	.01	.01	.00	.00	.00	.00	.00
fct:sample:linear:loading:items:f_cor	.00	.01	.00	.01	.01	.01	.00	.01	.01	.00	.00	.00
fct:sample:loading:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:linear:loading:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:linear:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:linear:loading:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.01	.01	.01
responses:sample:linear:loading:items:balance	.00	.01	.01	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:linear:loading:items:f_cor	.00	.00	.00	.00	.00	.00	.01	.01	.01	.00	.00	.00
responses:sample:loading:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.01	.01	.00	.00
sample:linear:loading:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:linear:loading:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.01	.00	.01	.00	.00	.00
fct:responses:sample:linear:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.01	.00	.00	.00	.00
fct:responses:sample:linear:loading:balance:f_cor	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01
fct:responses:sample:linear:loading:items:balance	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01
fct:responses:sample:linear:loading:items:f_cor	.01	.01	.01	.02	.01	.02	.01	.01	.01	.01	.01	.01
fct:responses:sample:loading:items:balance:f_cor	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01
fct:sample:linear:loading:items:balance:f_cor	.01	.00	.00	.00	.00	.00	.00	.00	.00	.01	.01	.01
responses:sample:linear:loading:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:sample:linear:loading:items:balance:f_cor	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01

Table 40. MAE Partial Eta Squared by Term Interaction (Part 3)

Term	walktrap_adapt_bic	louvain_adapt_bic	leiden_adapt_bic	walktrap_adapt_gic_3	louvain_adapt_gic_3	leiden_adapt_gic_3	walktrap_adapt_gic_4	louvain_adapt_gic_4	leiden_adapt_gic_4	walktrap_adapt_ebic	louvain_adapt_ebic	leiden_adapt_ebic
balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor	.12	.07	.06	.11	.05	.05	.09	.05	.04	.04	.02	.02
fct	.15	.05	.05	.16	.08	.08	.16	.09	.10	.15	.11	.11
items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
linear	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
loading	.28	.27	.27	.31	.29	.30	.43	.42	.42	.55	.55	.56
responses	.10	.06	.06	.07	.04	.04	.01	.00	.00	.00	.00	.00
sample	.21	.20	.21	.21	.23	.23	.28	.32	.32	.32	.34	.35
balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:balance	.00	.01	.01	.00	.01	.01	.00	.00	.00	.00	.00	.00
fct:f_cor	.06	.02	.02	.05	.01	.01	.03	.01	.01	.01	.00	.00
fct:items	.02	.08	.07	.02	.06	.06	.02	.04	.03	.01	.02	.02
fct:linear	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:loading	.02	.01	.01	.06	.03	.04	.12	.10	.10	.15	.14	.14
fct:responses	.03	.01	.01	.01	.01	.01	.00	.02	.02	.00	.01	.01
fct:sample	.01	.01	.01	.02	.02	.02	.05	.04	.04	.05	.05	.05

items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
items:f_cor	.01	.00	.00	.01	.00	.00	.00	.00	.00	.00	.00	.00
linear:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
linear:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
linear:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
linear:loading	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
loading:f_cor	.03	.02	.02	.03	.01	.01	.02	.01	.01	.01	.01	.01
loading:items	.01	.00	.00	.01	.01	.01	.01	.01	.01	.00	.00	.00
responses:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:items	.00	.01	.01	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:linear	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:loading	.01	.01	.01	.01	.01	.01	.01	.02	.02	.01	.02	.02
responses:sample	.04	.02	.02	.02	.01	.01	.00	.00	.01	.01	.01	.01
sample:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:f_cor	.00	.00	.00	.01	.00	.00	.00	.00	.00	.00	.00	.00
sample:items	.02	.01	.02	.03	.03	.03	.02	.02	.02	.00	.00	.00
sample:linear	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:loading	.05	.07	.09	.09	.13	.14	.26	.32	.34	.34	.37	.37
fct:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:items:f_cor	.01	.01	.01	.01	.01	.01	.01	.01	.01	.00	.00	.00
fct:linear:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:linear:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:linear:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:linear:loading	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:loading:balance	.00	.01	.01	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:loading:f_cor	.01	.00	.00	.01	.00	.00	.01	.00	.00	.00	.00	.00
fct:loading:items	.01	.02	.02	.00	.01	.01	.00	.01	.00	.00	.00	.00
fct:responses:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:items	.00	.01	.01	.01	.02	.02	.00	.01	.01	.00	.00	.00
fct:responses:linear	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:loading	.02	.02	.02	.02	.03	.03	.01	.02	.03	.01	.01	.01
fct:responses:sample	.01	.01	.01	.00	.02	.02	.01	.03	.03	.01	.02	.02
fct:sample:balance	.00	.01	.01	.00	.00	.00	.00	.01	.00	.00	.00	.00
fct:sample:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:sample:items	.01	.02	.02	.00	.01	.01	.00	.01	.01	.00	.00	.00
fct:sample:linear	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:sample:loading	.02	.01	.01	.01	.03	.02	.05	.11	.10	.06	.09	.10
items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
linear:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
linear:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
linear:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
linear:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
linear:loading:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.01	.00	.00	.00
linear:loading:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
loading:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
loading:items:f_cor	.00	.01	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:linear:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:linear:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:linear:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:linear:loading	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00

responses:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:loading:f_cor	.01	.00	.00	.01	.00	.00	.01	.00	.00	.00	.00	.00
responses:loading:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.01	.00	.00
responses:sample:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:items	.01	.02	.02	.01	.01	.01	.00	.01	.01	.00	.00	.00
responses:sample:linear	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:loading	.06	.05	.05	.06	.08	.08	.06	.07	.08	.02	.03	.03
sample:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:linear:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:linear:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:linear:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:linear:loading	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.01	.01	.01
sample:loading:f_cor	.02	.02	.01	.04	.02	.02	.02	.01	.01	.01	.01	.01
sample:loading:items	.02	.01	.01	.05	.02	.03	.03	.03	.03	.01	.00	.01
fct:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:linear:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:linear:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:linear:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:linear:loading:balance	.00	.00	.00	.00	.00	.00	.01	.00	.00	.01	.01	.01
fct:linear:loading:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:linear:loading:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:loading:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:loading:items:f_cor	.01	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:linear:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:linear:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:linear:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:linear:loading	.00	.00	.00	.01	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:loading:f_cor	.01	.00	.00	.01	.00	.00	.01	.00	.00	.00	.00	.00
fct:responses:loading:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.01	.00	.00
fct:responses:sample:balance	.01	.00	.00	.01	.00	.01	.01	.01	.01	.00	.01	.01
fct:responses:sample:f_cor	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01
fct:responses:sample:items	.01	.01	.01	.01	.01	.01	.01	.01	.01	.00	.01	.00
fct:responses:sample:linear	.00	.01	.00	.00	.00	.00	.00	.00	.00	.00	.01	.01
fct:responses:sample:loading	.04	.02	.02	.04	.03	.03	.02	.02	.02	.02	.02	.02
fct:sample:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:sample:items:balance	.00	.00	.00	.00	.00	.00	.01	.01	.01	.00	.00	.00
fct:sample:items:f_cor	.01	.01	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:sample:linear:balance	.00	.00	.00	.00	.00	.00	.00	.01	.00	.00	.00	.00
fct:sample:linear:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:sample:linear:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:sample:linear:loading	.00	.00	.01	.00	.01	.01	.01	.00	.00	.00	.00	.00
fct:sample:loading:balance	.01	.01	.01	.00	.01	.01	.01	.01	.01	.01	.01	.01
fct:sample:loading:f_cor	.01	.01	.01	.02	.01	.01	.02	.01	.01	.01	.00	.00
fct:sample:loading:items	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01
linear:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
linear:loading:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
linear:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
linear:loading:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
loading:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00

responses:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:linear:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:linear:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:linear:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:linear:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:linear:loading:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:linear:loading:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:loading:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:loading:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:items:balance	.00	.00	.00	.00	.00	.00	.01	.00	.00	.00	.00	.00
responses:sample:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:linear:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:linear:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:linear:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:linear:loading	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:loading:balance	.01	.00	.01	.01	.00	.01	.00	.00	.00	.00	.00	.00
responses:sample:loading:f_cor	.01	.01	.01	.01	.01	.02	.02	.02	.01	.01	.01	.01
responses:sample:loading:items	.00	.01	.01	.00	.00	.01	.00	.00	.00	.00	.00	.00
sample:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:linear:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:linear:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:linear:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:linear:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:linear:loading:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.01	.00	.01	.01
sample:linear:loading:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:loading:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:loading:items:f_cor	.01	.01	.01	.01	.01	.01	.01	.00	.00	.00	.00	.00
fct:linear:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:linear:loading:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:linear:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:linear:loading:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:loading:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:linear:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:linear:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:linear:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:linear:loading:balance	.01	.01	.01	.01	.01	.01	.01	.00	.00	.00	.00	.00
fct:responses:linear:loading:f_cor	.01	.00	.00	.00	.00	.00	.01	.01	.01	.00	.00	.00
fct:responses:linear:loading:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:loading:balance:f_cor	.01	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:loading:items:balance	.01	.01	.00	.00	.01	.01	.00	.00	.00	.00	.00	.00
fct:responses:loading:items:f_cor	.01	.01	.01	.00	.00	.01	.00	.00	.00	.00	.00	.00
fct:responses:sample:balance:f_cor	.01	.00	.00	.00	.00	.00	.01	.01	.01	.00	.01	.01
fct:responses:sample:items:balance	.00	.00	.00	.00	.00	.00	.01	.01	.01	.01	.01	.01
fct:responses:sample:items:f_cor	.01	.01	.01	.01	.01	.01	.00	.01	.01	.00	.00	.00
fct:responses:sample:linear:balance	.00	.01	.00	.00	.00	.00	.00	.01	.01	.00	.00	.00
fct:responses:sample:linear:f_cor	.00	.01	.00	.00	.00	.00	.01	.00	.00	.00	.00	.00
fct:responses:sample:linear:items	.00	.00	.00	.00	.00	.00	.01	.00	.00	.01	.00	.00
fct:responses:sample:linear:loading	.01	.01	.01	.01	.01	.01	.00	.00	.00	.01	.01	.01
fct:responses:sample:loading:balance	.02	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01
fct:responses:sample:loading:f_cor	.01	.02	.02	.02	.02	.01	.02	.02	.02	.01	.01	.01
fct:responses:sample:loading:items	.01	.02	.02	.01	.01	.01	.02	.02	.02	.01	.02	.01
fct:sample:items:balance:f_cor	.00	.01	.01	.00	.00	.00	.00	.01	.01	.01	.01	.01
fct:sample:linear:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:sample:linear:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00

fct:sample:linear:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:sample:linear:loading:balance	.00	.00	.00	.01	.00	.01	.01	.01	.01	.01	.01	.00
fct:sample:linear:loading:f_cor	.00	.00	.00	.00	.00	.00	.00	.01	.01	.01	.01	.01
fct:sample:linear:loading:items	.01	.01	.01	.01	.01	.01	.00	.01	.01	.01	.01	.01
fct:sample:loading:balance:f_cor	.01	.01	.01	.01	.01	.01	.01	.00	.00	.00	.00	.00
fct:sample:loading:items:balance	.00	.00	.01	.00	.01	.01	.01	.02	.02	.00	.01	.01
fct:sample:loading:items:f_cor	.02	.02	.02	.01	.01	.01	.01	.01	.01	.01	.01	.01
linear:loading:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:linear:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:linear:loading:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:linear:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:linear:loading:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:loading:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.01	.00	.00	.00	.00
responses:sample:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.01	.00	.00
responses:sample:linear:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:linear:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:linear:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:linear:loading:balance	.00	.00	.00	.00	.01	.01	.00	.00	.01	.00	.00	.00
responses:sample:linear:loading:f_cor	.00	.00	.00	.00	.00	.00	.00	.01	.01	.00	.00	.00
responses:sample:linear:loading:items	.00	.00	.00	.00	.00	.00	.00	.00	.01	.00	.01	.01
responses:sample:loading:balance:f_cor	.01	.01	.01	.01	.01	.01	.00	.01	.00	.00	.00	.00
responses:sample:loading:items:balance	.00	.00	.00	.00	.00	.00	.01	.01	.01	.00	.00	.00
responses:sample:loading:items:f_cor	.00	.01	.01	.00	.01	.01	.00	.01	.01	.00	.00	.00
sample:linear:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:linear:loading:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:linear:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:linear:loading:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:loading:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:linear:loading:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.01	.01
fct:responses:linear:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:linear:loading:balance:f_cor	.00	.00	.00	.01	.00	.00	.01	.01	.00	.01	.01	.01
fct:responses:linear:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:linear:loading:items:f_cor	.00	.00	.01	.01	.00	.00	.01	.01	.01	.00	.00	.00
fct:responses:loading:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.01	.00	.00	.00	.01	.01
fct:responses:sample:items:balance:f_cor	.01	.00	.00	.01	.00	.00	.01	.01	.01	.01	.00	.00
fct:responses:sample:linear:balance:f_cor	.00	.00	.01	.01	.01	.01	.00	.00	.00	.00	.00	.00
fct:responses:sample:linear:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.01
fct:responses:sample:linear:items:f_cor	.00	.01	.00	.00	.01	.01	.01	.01	.01	.00	.01	.01
fct:responses:sample:linear:loading:balance	.01	.01	.01	.01	.01	.00	.01	.01	.01	.00	.00	.01
fct:responses:sample:linear:loading:f_cor	.01	.01	.01	.01	.01	.01	.02	.01	.01	.01	.01	.01
fct:responses:sample:linear:loading:items	.01	.01	.01	.01	.01	.01	.01	.00	.00	.01	.00	.01
fct:responses:sample:loading:balance:f_cor	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01
fct:responses:sample:loading:items:balance	.01	.01	.01	.01	.01	.01	.02	.01	.01	.02	.01	.01
fct:responses:sample:loading:items:f_cor	.02	.03	.03	.01	.01	.02	.01	.02	.02	.01	.01	.01
fct:sample:linear:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:sample:linear:loading:balance:f_cor	.00	.01	.01	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:sample:linear:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:sample:linear:loading:items:f_cor	.01	.00	.01	.01	.00	.00	.00	.01	.01	.00	.00	.00
fct:sample:loading:items:balance:f_cor	.01	.01	.01	.01	.01	.01	.00	.01	.01	.01	.01	.01
responses:linear:loading:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:linear:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:linear:loading:balance:f_cor	.00	.00	.00	.00	.00	.00	.01	.00	.00	.00	.00	.00
responses:sample:linear:loading:items:balance	.01	.00	.01	.00	.01	.01	.00	.01	.01	.00	.00	.00
responses:sample:linear:loading:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.01	.01	.00	.00	.00
responses:sample:loading:items:balance:f_cor	.00	.00	.00	.01	.00	.00	.01	.00	.00	.01	.01	.01
sample:linear:loading:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:linear:loading:items:balance:f_cor	.01	.00	.01	.01	.01	.01	.00	.01	.00	.00	.00	.00
fct:responses:sample:linear:items:balance:f_cor	.01	.01	.00	.01	.00	.00	.01	.01	.01	.01	.01	.01

fct:responses:sample:linear:loading:balance:f_cor	.01	.01	.01	.01	.02	.01	.01	.01	.01	.01	.01	.01
fct:responses:sample:linear:loading:items:balance	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01
fct:responses:sample:linear:loading:items:f_cor	.01	.01	.01	.01	.01	.01	.02	.02	.02	.01	.01	.01
fct:responses:sample:loading:items:balance:f_cor	.01	.02	.02	.01	.01	.02	.01	.01	.02	.01	.01	.01
fct:sample:linear:loading:items:balance:f_cor	.01	.00	.00	.01	.00	.01	.01	.00	.00	.00	.00	.00
responses:sample:linear:loading:items:balance:f_cor	.00	.00	.00	.01	.01	.01	.01	.01	.01	.00	.00	.00
fct:responses:sample:linear:loading:items:balance:f_cor	.01	.01	.01	.02	.02	.01	.02	.02	.02	.01	.01	.01

Table 41. MAE Partial Eta Squared by Term Interaction (Part 4)

Term	walktrap_log_bic	louvain_log_bic	leiden_log_bic	walktrap_log_gic_3	louvain_log_gic_3	leiden_log_gic_3	walktrap_log_gic_4	louvain_log_gic_4	leiden_log_gic_4	walktrap_log_ebic	louvain_log_ebic	leiden_log_ebic
balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor	.10	.07	.06	.10	.05	.05	.07	.04	.04	.03	.01	.01
fct	.12	.04	.04	.12	.05	.05	.13	.08	.07	.14	.09	.09
items	.00	.00	.00	.00	.00	.00	.00	.01	.01	.00	.00	.00
linear	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
loading	.28	.26	.26	.29	.27	.28	.43	.41	.41	.56	.57	.57
responses	.09	.07	.07	.07	.04	.04	.01	.00	.00	.00	.00	.00
sample	.21	.22	.22	.21	.21	.23	.30	.32	.32	.36	.38	.38
balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:balance	.00	.01	.01	.00	.01	.01	.00	.00	.01	.00	.00	.00
fct:f_cor	.04	.01	.01	.03	.01	.01	.02	.00	.00	.01	.00	.00
fct:items	.01	.07	.07	.01	.06	.07	.01	.03	.03	.01	.01	.02
fct:linear	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:loading	.02	.01	.00	.04	.01	.02	.11	.09	.08	.15	.15	.14
fct:responses	.03	.01	.01	.01	.01	.01	.00	.02	.02	.00	.02	.02
fct:sample	.01	.00	.01	.01	.01	.01	.05	.04	.04	.06	.05	.05
items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
linear:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
linear:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
linear:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
linear:loading	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.01	.01
loading:f_cor	.03	.02	.02	.03	.01	.01	.02	.01	.01	.01	.01	.00
loading:items	.01	.00	.00	.01	.01	.01	.02	.02	.02	.00	.00	.00
responses:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:items	.01	.01	.01	.00	.01	.01	.00	.00	.00	.00	.00	.00
responses:linear	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:loading	.01	.01	.01	.01	.01	.01	.01	.02	.02	.02	.04	.04
responses:sample	.03	.02	.02	.02	.01	.01	.01	.01	.01	.01	.01	.01
sample:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:f_cor	.00	.00	.00	.00	.00	.01	.00	.00	.00	.00	.00	.00
sample:items	.02	.02	.02	.03	.03	.04	.03	.04	.04	.01	.01	.01
sample:linear	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:loading	.05	.07	.08	.08	.10	.12	.26	.30	.31	.37	.40	.40
fct:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.01	.00	.00
fct:items:f_cor	.01	.01	.01	.00	.01	.01	.00	.01	.01	.00	.01	.01

fct:linear:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:linear:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:linear:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:linear:loading	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:loading:balance	.00	.01	.01	.01	.01	.01	.00	.00	.00	.00	.00	.00
fct:loading:f_cor	.01	.00	.00	.01	.00	.00	.01	.00	.00	.00	.00	.00
fct:loading:items	.01	.02	.02	.00	.01	.01	.00	.00	.00	.00	.00	.00
fct:responses:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:items	.00	.01	.01	.00	.02	.02	.00	.01	.01	.00	.01	.01
fct:responses:linear	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:loading	.01	.02	.02	.02	.03	.03	.02	.03	.03	.01	.02	.02
fct:responses:sample	.01	.00	.01	.00	.01	.01	.02	.03	.03	.02	.03	.03
fct:sample:balance	.00	.01	.01	.00	.01	.01	.00	.00	.00	.00	.00	.00
fct:sample:f_cor	.00	.00	.00	.00	.00	.01	.01	.01	.00	.00	.00	.00
fct:sample:items	.00	.01	.01	.00	.01	.01	.00	.00	.00	.00	.00	.00
fct:sample:linear	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:sample:loading	.01	.01	.02	.00	.01	.01	.06	.11	.11	.09	.13	.13
items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
linear:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
linear:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
linear:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
linear:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
linear:loading:f_cor	.00	.00	.00	.00	.00	.00	.00	.01	.01	.00	.00	.00
linear:loading:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
loading:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
loading:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:linear:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:linear:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:linear:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:linear:loading	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:loading:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:loading:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:balance	.00	.00	.00	.00	.00	.00	.00	.01	.00	.00	.00	.00
responses:sample:f_cor	.00	.00	.00	.00	.00	.00	.00	.01	.00	.00	.00	.00
responses:sample:items	.01	.01	.01	.01	.01	.01	.00	.00	.00	.00	.00	.00
responses:sample:linear	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:loading	.05	.07	.05	.05	.07	.07	.09	.09	.10	.05	.05	.06
sample:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:linear:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:linear:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:linear:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:linear:loading	.00	.00	.00	.00	.00	.01	.00	.00	.00	.00	.00	.00
sample:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:loading:f_cor	.02	.02	.02	.02	.02	.02	.03	.02	.02	.03	.02	.02
sample:loading:items	.02	.01	.01	.04	.03	.04	.04	.03	.03	.01	.01	.01
fct:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:linear:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:linear:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:linear:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:linear:loading:balance	.00	.00	.00	.00	.00	.00	.01	.00	.00	.00	.00	.00

fct:linear:loading:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:linear:loading:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:loading:balance:f_cor	.00	.00	.00	.01	.00	.00	.00	.00	.00	.00	.00	.00
fct:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.01	.00	.00
fct:loading:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:linear:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:linear:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:linear:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:linear:loading	.01	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.01	.00	.00
fct:responses:loading:f_cor	.01	.00	.00	.00	.00	.00	.00	.00	.00	.01	.00	.00
fct:responses:loading:items	.00	.00	.00	.00	.00	.00	.01	.00	.00	.01	.01	.01
fct:responses:sample:balance	.00	.00	.00	.00	.00	.00	.01	.00	.01	.01	.01	.01
fct:responses:sample:f_cor	.00	.01	.01	.00	.01	.01	.01	.01	.01	.01	.01	.01
fct:responses:sample:items	.00	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01
fct:responses:sample:linear	.01	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:sample:loading	.02	.02	.01	.03	.02	.02	.03	.03	.03	.03	.03	.03
fct:sample:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:sample:items:balance	.00	.00	.00	.00	.00	.00	.01	.01	.01	.00	.00	.00
fct:sample:items:f_cor	.01	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:sample:linear:balance	.00	.00	.00	.00	.01	.01	.01	.01	.01	.00	.00	.00
fct:sample:linear:f_cor	.00	.00	.00	.00	.00	.00	.01	.00	.00	.00	.00	.00
fct:sample:linear:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:sample:linear:loading	.01	.00	.00	.01	.00	.00	.01	.00	.00	.00	.00	.00
fct:sample:loading:balance	.00	.01	.01	.01	.01	.01	.01	.00	.00	.01	.01	.01
fct:sample:loading:f_cor	.01	.01	.01	.01	.02	.02	.02	.01	.01	.01	.01	.01
fct:sample:loading:items	.01	.01	.01	.01	.01	.01	.01	.01	.01	.00	.01	.01
linear:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
linear:loading:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
linear:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
linear:loading:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
loading:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:linear:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:linear:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:linear:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:linear:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:linear:loading:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:linear:loading:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:loading:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:loading:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:linear:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:linear:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:linear:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:linear:loading	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:loading:balance	.00	.00	.00	.00	.00	.01	.00	.01	.01	.00	.00	.00
responses:sample:loading:f_cor	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01
responses:sample:loading:items	.00	.01	.00	.00	.00	.01	.00	.00	.00	.00	.00	.00
sample:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:linear:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:linear:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00

sample:linear:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:linear:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:linear:loading:f_cor	.00	.00	.00	.00	.00	.00	.00	.01	.00	.00	.00	.00
sample:linear:loading:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:loading:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.01	.00	.00	.00	.00
sample:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:loading:items:f_cor	.01	.01	.01	.01	.01	.01	.01	.00	.00	.00	.00	.00
fct:linear:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:linear:loading:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:linear:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:linear:loading:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:loading:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:linear:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:linear:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:linear:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:linear:loading:balance	.01	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:linear:loading:f_cor	.00	.00	.00	.00	.00	.00	.01	.01	.01	.00	.00	.00
fct:responses:linear:loading:items	.00	.00	.00	.00	.01	.01	.01	.01	.01	.00	.00	.00
fct:responses:loading:balance:f_cor	.01	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.01	.01	.01
fct:responses:loading:items:f_cor	.00	.01	.01	.00	.01	.01	.00	.00	.00	.00	.00	.00
fct:responses:sample:balance:f_cor	.01	.01	.01	.00	.00	.01	.00	.00	.00	.01	.01	.01
fct:responses:sample:items:balance	.00	.00	.00	.00	.01	.00	.01	.01	.00	.01	.01	.00
fct:responses:sample:items:f_cor	.00	.00	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01
fct:responses:sample:linear:balance	.00	.01	.01	.01	.01	.01	.01	.01	.01	.01	.00	.00
fct:responses:sample:linear:f_cor	.00	.01	.00	.00	.01	.00	.00	.01	.00	.00	.00	.00
fct:responses:sample:linear:items	.00	.00	.00	.01	.00	.01	.01	.00	.00	.00	.00	.00
fct:responses:sample:linear:loading	.01	.01	.00	.01	.01	.01	.01	.00	.01	.01	.01	.01
fct:responses:sample:loading:balance	.02	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01
fct:responses:sample:loading:f_cor	.01	.01	.01	.01	.01	.01	.02	.02	.02	.01	.02	.01
fct:responses:sample:loading:items	.01	.01	.02	.02	.02	.01	.02	.01	.01	.02	.02	.02
fct:sample:items:balance:f_cor	.00	.01	.01	.00	.01	.01	.00	.01	.01	.00	.01	.00
fct:sample:linear:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:sample:linear:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:sample:linear:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:sample:linear:loading:balance	.00	.00	.00	.01	.00	.01	.01	.01	.01	.01	.01	.01
fct:sample:linear:loading:f_cor	.01	.00	.00	.01	.00	.00	.01	.01	.01	.00	.00	.00
fct:sample:linear:loading:items	.01	.01	.00	.01	.01	.01	.00	.01	.01	.00	.00	.00
fct:sample:loading:balance:f_cor	.00	.01	.00	.00	.01	.00	.00	.00	.00	.00	.00	.00
fct:sample:loading:items:balance	.00	.01	.01	.00	.00	.01	.01	.01	.01	.00	.01	.01
fct:sample:loading:items:f_cor	.01	.02	.01	.01	.01	.01	.01	.01	.01	.00	.01	.01
linear:loading:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:linear:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:linear:loading:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:linear:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:linear:loading:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:loading:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.01	.00	.00	.00	.00	.00
responses:sample:linear:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:linear:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:linear:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:linear:loading:balance	.01	.01	.01	.00	.00	.01	.01	.01	.01	.00	.00	.00
responses:sample:linear:loading:f_cor	.00	.00	.00	.00	.00	.00	.00	.01	.01	.00	.00	.00
responses:sample:linear:loading:items	.00	.00	.00	.00	.01	.00	.00	.00	.00	.00	.00	.00
responses:sample:loading:balance:f_cor	.01	.00	.01	.01	.01	.01	.00	.00	.00	.01	.00	.00
responses:sample:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.01	.01	.01
responses:sample:loading:items:f_cor	.00	.01	.01	.00	.00	.00	.01	.01	.01	.00	.01	.00

sample:linear:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:linear:loading:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:linear:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:linear:loading:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:loading:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:linear:loading:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:linear:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:linear:loading:balance:f_cor	.00	.00	.00	.00	.00	.00	.01	.00	.00	.00	.00	.00
fct:responses:linear:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:linear:loading:items:f_cor	.01	.00	.00	.00	.00	.01	.01	.00	.01	.00	.00	.00
fct:responses:loading:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.01	.00	.00	.00
fct:responses:sample:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.01	.01	.01	.01	.01	.01
fct:responses:sample:linear:balance:f_cor	.00	.01	.01	.00	.00	.01	.00	.01	.00	.00	.00	.00
fct:responses:sample:linear:items:balance	.01	.00	.00	.00	.00	.00	.01	.00	.00	.01	.01	.01
fct:responses:sample:linear:items:f_cor	.01	.00	.00	.01	.01	.00	.01	.01	.01	.00	.00	.00
fct:responses:sample:linear:loading:balance	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01
fct:responses:sample:linear:loading:f_cor	.01	.01	.01	.01	.01	.01	.01	.02	.02	.01	.01	.01
fct:responses:sample:linear:loading:items	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01
fct:responses:sample:loading:balance:f_cor	.02	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01
fct:responses:sample:loading:items:balance	.01	.01	.01	.01	.01	.01	.01	.01	.01	.02	.01	.01
fct:responses:sample:loading:items:f_cor	.01	.02	.02	.02	.01	.01	.01	.01	.02	.01	.01	.01
fct:sample:linear:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:sample:linear:loading:balance:f_cor	.00	.00	.00	.01	.00	.01	.00	.00	.00	.00	.00	.00
fct:sample:linear:loading:items:balance	.00	.00	.01	.01	.00	.00	.00	.00	.00	.01	.01	.00
fct:sample:linear:loading:items:f_cor	.01	.01	.01	.00	.00	.01	.01	.01	.01	.00	.00	.00
fct:sample:loading:items:balance:f_cor	.00	.01	.01	.00	.01	.01	.00	.00	.01	.00	.01	.01
responses:linear:loading:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:linear:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:linear:loading:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:linear:loading:items:balance	.00	.00	.01	.00	.00	.00	.00	.01	.01	.01	.00	.00
responses:sample:linear:loading:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:loading:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.01	.01	.00	.00	.00	.00
sample:linear:loading:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:linear:loading:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.01	.01	.00	.00	.00
fct:responses:sample:linear:items:balance:f_cor	.00	.00	.01	.00	.00	.00	.01	.01	.01	.01	.01	.00
fct:responses:sample:linear:loading:balance:f_cor	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01
fct:responses:sample:linear:loading:items:balance	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01
fct:responses:sample:linear:loading:items:f_cor	.02	.01	.01	.01	.01	.01	.01	.01	.01	.01	.00	.00
fct:responses:sample:loading:items:balance:f_cor	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01
fct:sample:linear:loading:items:balance:f_cor	.01	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:linear:loading:items:balance:f_cor	.00	.00	.00	.00	.01	.01	.00	.00	.00	.00	.00	.00
fct:responses:sample:linear:loading:items:balance:f_cor	.01	.01	.01	.01	.01	.01	.02	.02	.02	.01	.01	.01

Table 42. MAE Partial Eta Squared by Term Interaction (Part 5)

Term	R2Z_walktrap	R2Z_louvain	R2Z_leiden	fspe	fspe_none	fspe_geominQ	fspe_varimax	fspe_oblimin	EGAnet	PA_FA	PA_FA_none	PA_FA_geominQ	PA_FA_varimax	PA_FA_oblimin	PA_PC	PA_PC_none	PA_PC_geominQ	PA_PC_varimax	PA_PC_oblimin
balance	.00	.00	.00	.01	.00	.00	.00	.00	.00	.01	.00	.00	.00	.00	.01	.00	.00	.00	.00
f_cor	.27	.08	.08	.33	.00	.00	.00	.00	.14	.10	.00	.00	.00	.00	.44	.00	.00	.00	.00
fct	.63	.31	.32	.28	###	###	###	###	.11	.18	###	###	###	###	.30	###	###	###	###
items	.01	.01	.02	.08	.00	.00	.00	.00	.03	.04	.00	.00	.00	.00	.07	.00	.00	.00	.00
linear	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
loading	.55	.29	.30	.53	.00	.00	.00	.00	.37	.68	.00	.00	.00	.00	.26	.00	.00	.00	.00
responses	.10	.04	.03	.12	.00	.00	.00	.00	.00	.63	.00	.00	.00	.00	.01	.00	.00	.00	.00

sample	.43	.21	.22	.24	.00	.00	.00	.00	.19	.13	.00	.00	.00	.00	.13	.00	.00	.00	.00
balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor	.12	.02	.02	.15	.00	.00	.00	.00	.04	.07	.00	.00	.00	.00	.15	.00	.00	.00	.00
fct:items	.01	.12	.12	.04	.00	.00	.00	.00	.01	.07	.00	.00	.00	.00	.01	.00	.00	.00	.00
fct:linear	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:loading	.29	.08	.09	.26	.00	.00	.00	.00	.09	.11	.00	.00	.00	.00	.07	.00	.00	.00	.00
fct:responses	.03	.00	.01	.03	.00	.00	.00	.00	.00	.19	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:sample	.20	.05	.06	.10	.00	.00	.00	.00	.02	.04	.00	.00	.00	.00	.03	.00	.00	.00	.00
items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
items:f_cor	.01	.00	.01	.01	.00	.00	.00	.00	.02	.05	.00	.00	.00	.00	.14	.00	.00	.00	.00
linear:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
linear:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
linear:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
linear:loading	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.03	.00	.00	.00	.00	.00	.00	.00	.00	.00
loading:f_cor	.03	.01	.01	.22	.00	.00	.00	.00	.02	.02	.00	.00	.00	.00	.01	.00	.00	.00	.00
loading:items	.02	.01	.01	.05	.00	.00	.00	.00	.01	.01	.00	.00	.00	.00	.05	.00	.00	.00	.00
responses:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.01	.00	.00	.00	.00
responses:f_cor	.00	.00	.00	.03	.00	.00	.00	.00	.00	.07	.00	.00	.00	.00	.10	.00	.00	.00	.00
responses:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.40	.00	.00	.00	.00	.07	.00	.00	.00	.00
responses:linear	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:loading	.01	.00	.00	.05	.00	.00	.00	.00	.02	.48	.00	.00	.00	.00	.06	.00	.00	.00	.00
responses:sample	.00	.00	.00	.01	.00	.00	.00	.00	.03	.04	.00	.00	.00	.00	.01	.00	.00	.00	.00
sample:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:f_cor	.01	.00	.00	.03	.00	.00	.00	.00	.00	.01	.00	.00	.00	.00	.01	.00	.00	.00	.00
sample:items	.01	.01	.01	.01	.00	.00	.00	.00	.01	.01	.00	.00	.00	.00	.01	.00	.00	.00	.00
sample:linear	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:loading	.07	.03	.03	.14	.00	.00	.00	.00	.20	.03	.00	.00	.00	.00	.04	.00	.00	.00	.00
fct:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:items:f_cor	.00	.01	.01	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.04	.00	.00	.00	.00
fct:linear:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:linear:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:linear:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:linear:loading	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:loading:balance	.00	.01	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:loading:f_cor	.01	.01	.01	.08	.01	.01	.01	.01	.01	.02	.01	.01	.01	.01	.00	.01	.01	.01	.01
fct:loading:items	.02	.05	.05	.01	.00	.00	.00	.00	.00	.07	.00	.00	.00	.00	.02	.00	.00	.00	.00
fct:responses:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:f_cor	.00	.00	.00	.01	.01	.01	.01	.01	.00	.01	.01	.01	.01	.01	.05	.01	.01	.01	.01
fct:responses:items	.00	.01	.01	.00	.00	.00	.00	.00	.00	.10	.00	.00	.00	.00	.03	.00	.00	.00	.00
fct:responses:linear	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:loading	.00	.01	.00	.01	.01	.01	.01	.01	.02	.14	.01	.01	.01	.01	.01	.01	.01	.01	.01
fct:responses:sample	.01	.01	.01	.00	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01	.00	.01	.01	.01	.01
fct:sample:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:sample:f_cor	.01	.01	.00	.01	.01	.01	.01	.01	.00	.00	.01	.01	.01	.01	.00	.01	.01	.01	.01
fct:sample:items	.01	.01	.02	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:sample:linear	.00	.00	.01	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:sample:loading	.06	.02	.02	.04	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01
items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
linear:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
linear:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
linear:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
linear:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
linear:loading:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
linear:loading:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
loading:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00

loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
loading:items:f_cor	.01	.00	.00	.01	.00	.00	.00	.00	.01	.04	.00	.00	.00	.00	.01	.00	.00	.00	.00
responses:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.04	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:linear:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:linear:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:linear:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:linear:loading	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.01	.00	.00	.00	.00
responses:loading:f_cor	.01	.01	.01	.01	.00	.00	.00	.00	.01	.02	.00	.00	.00	.00	.08	.00	.00	.00	.00
responses:loading:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.31	.00	.00	.00	.00	.10	.00	.00	.00	.00
responses:sample:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.01	.00	.00	.00	.00	.02	.00	.00	.00	.00
responses:sample:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.03	.00	.00	.00	.00	.01	.00	.00	.00	.00
responses:sample:linear	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:loading	.03	.01	.01	.01	.00	.00	.00	.00	.09	.02	.00	.00	.00	.00	.02	.00	.00	.00	.00
sample:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:items:balance	.00	.00	.00	.00	.01	.01	.01	.01	.00	.00	.01	.01	.01	.01	.00	.01	.01	.01	.01
sample:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.01	.01	.00	.00	.00	.00	.01	.00	.00	.00	.00
sample:linear:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:linear:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:linear:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:linear:loading	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:loading:f_cor	.07	.03	.03	.03	.00	.00	.00	.00	.03	.00	.00	.00	.00	.00	.01	.00	.00	.00	.00
sample:loading:items	.01	.01	.01	.00	.00	.00	.00	.00	.01	.01	.00	.00	.00	.00	.01	.00	.00	.00	.00
fct:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:linear:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:linear:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:linear:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:linear:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.01	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:linear:loading:f_cor	.00	.00	.00	.00	.01	.01	.01	.01	.00	.00	.01	.01	.01	.01	.00	.01	.01	.01	.01
fct:linear:loading:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:loading:balance:f_cor	.00	.00	.00	.00	.01	.01	.01	.01	.00	.00	.01	.01	.01	.01	.00	.01	.01	.01	.01
fct:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.01	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:loading:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.01	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:balance:f_cor	.00	.00	.00	.00	.01	.01	.01	.01	.00	.00	.01	.01	.01	.01	.00	.01	.01	.01	.01
fct:responses:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.01	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.02	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:linear:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:linear:f_cor	.00	.00	.00	.00	.01	.01	.01	.01	.00	.00	.01	.01	.01	.01	.00	.01	.01	.01	.01
fct:responses:linear:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:linear:loading	.00	.00	.00	.00	.01	.01	.01	.01	.00	.00	.01	.01	.01	.01	.00	.01	.01	.01	.01
fct:responses:loading:balance	.00	.00	.01	.00	.01	.01	.01	.01	.00	.00	.01	.01	.01	.01	.00	.01	.01	.01	.01
fct:responses:loading:f_cor	.01	.01	.01	.01	.01	.01	.01	.01	.01	.00	.01	.01	.01	.01	.04	.01	.01	.01	.01
fct:responses:loading:items	.00	.01	.01	.00	.00	.00	.00	.00	.00	.06	.00	.00	.00	.00	.03	.00	.00	.00	.00
fct:responses:sample:balance	.00	.00	.00	.01	.01	.01	.01	.01	.01	.00	.01	.01	.01	.01	.00	.01	.01	.01	.01
fct:responses:sample:f_cor	.01	.00	.00	.00	.02	.02	.02	.02	.01	.01	.02	.02	.02	.02	.01	.02	.02	.02	.02
fct:responses:sample:items	.01	.01	.00	.00	.00	.00	.00	.00	.01	.01	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:sample:linear	.00	.01	.00	.01	.01	.01	.01	.01	.01	.00	.01	.01	.01	.01	.00	.01	.01	.01	.01
fct:responses:sample:loading	.02	.01	.01	.01	.02	.02	.02	.02	.03	.01	.02	.02	.02	.02	.01	.02	.02	.02	.02
fct:sample:balance:f_cor	.00	.00	.01	.00	.01	.01	.01	.01	.00	.00	.01	.01	.01	.01	.00	.01	.01	.01	.01
fct:sample:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:sample:items:f_cor	.01	.00	.00	.00	.00	.00	.00	.00	.00	.01	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:sample:linear:balance	.00	.01	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:sample:linear:f_cor	.01	.00	.00	.00	.01	.01	.01	.01	.00	.00	.01	.01	.01	.01	.00	.01	.01	.01	.01
fct:sample:linear:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00

fct:sample:linear:loading	.00	.00	.01	.00	.01	.01	.01	.01	.00	.00	.01	.01	.01	.01	.00	.01	.01	.01	.01
fct:sample:loading:balance	.00	.01	.01	.00	.01	.01	.01	.01	.00	.01	.01	.01	.01	.01	.00	.01	.01	.01	.01
fct:sample:loading:f_cor	.04	.02	.02	.02	.02	.02	.02	.02	.01	.00	.02	.02	.02	.02	.01	.02	.02	.02	.02
fct:sample:loading:items	.01	.01	.01	.00	.00	.00	.00	.00	.01	.01	.00	.00	.00	.00	.00	.00	.00	.00	.00
linear:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
linear:loading:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
linear:loading:items:balance	.00	.00	.00	.00	.01	.01	.01	.01	.00	.00	.01	.01	.01	.01	.00	.01	.01	.01	.01
linear:loading:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
loading:items:balance:f_cor	.00	.00	.00	.00	.01	.01	.01	.01	.00	.00	.01	.01	.01	.01	.00	.01	.01	.01	.01
responses:items:balance:f_cor	.00	.00	.00	.00	.01	.01	.01	.01	.00	.00	.01	.01	.01	.01	.00	.01	.01	.01	.01
responses:linear:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:linear:items:balance	.00	.00	.00	.00	.01	.01	.01	.01	.00	.00	.01	.01	.01	.01	.00	.01	.01	.01	.01
responses:linear:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:linear:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:linear:loading:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:linear:loading:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:loading:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:loading:items:balance	.00	.00	.00	.00	.01	.01	.01	.01	.00	.00	.01	.01	.01	.01	.00	.01	.01	.01	.01
responses:loading:items:f_cor	.00	.00	.00	.01	.00	.00	.00	.00	.00	.01	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:items:balance	.00	.00	.00	.00	.01	.01	.01	.01	.00	.00	.01	.01	.01	.01	.00	.01	.01	.01	.01
responses:sample:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:linear:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:linear:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:linear:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:linear:loading	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:loading:balance	.00	.00	.00	.01	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:loading:f_cor	.01	.00	.00	.04	.00	.00	.00	.00	.01	.02	.00	.00	.00	.00	.01	.00	.00	.00	.00
responses:sample:loading:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.01	.00	.00	.00	.00	.01	.00	.00	.00	.00
sample:items:balance:f_cor	.00	.00	.00	.00	.01	.01	.01	.01	.00	.00	.01	.01	.01	.01	.00	.01	.01	.01	.01
sample:linear:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:linear:items:balance	.00	.00	.00	.00	.01	.01	.01	.01	.00	.00	.01	.01	.01	.01	.00	.01	.01	.01	.01
sample:linear:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:linear:loading:balance	.00	.00	.01	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:linear:loading:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:linear:loading:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:loading:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:loading:items:balance	.00	.00	.00	.00	.01	.01	.01	.01	.00	.00	.01	.01	.01	.01	.00	.01	.01	.01	.01
sample:loading:items:f_cor	.00	.00	.00	.03	.00	.00	.00	.00	.01	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:linear:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:linear:loading:balance:f_cor	.00	.00	.00	.00	.01	.01	.01	.01	.00	.00	.01	.01	.01	.01	.00	.01	.01	.01	.01
fct:linear:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:linear:loading:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:loading:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:linear:balance:f_cor	.00	.00	.00	.00	.01	.01	.01	.01	.00	.00	.01	.01	.01	.01	.00	.01	.01	.01	.01
fct:responses:linear:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:linear:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:linear:loading:balance	.00	.00	.01	.00	.01	.01	.01	.01	.00	.00	.01	.01	.01	.01	.00	.01	.01	.01	.01
fct:responses:linear:loading:f_cor	.00	.00	.00	.00	.02	.02	.02	.02	.00	.00	.02	.02	.02	.02	.00	.02	.02	.02	.02
fct:responses:linear:loading:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:loading:balance:f_cor	.00	.00	.00	.00	.02	.02	.02	.02	.00	.00	.02	.02	.02	.02	.00	.02	.02	.02	.02
fct:responses:loading:items:balance	.01	.00	.00	.00	.00	.00	.00	.00	.00	.01	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:loading:items:f_cor	.00	.01	.00	.01	.00	.00	.00	.00	.00	.01	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:sample:balance:f_cor	.00	.00	.01	.01	.02	.02	.02	.02	.00	.00	.02	.02	.02	.02	.00	.02	.02	.02	.02
fct:responses:sample:items:balance	.00	.00	.01	.01	.00	.00	.00	.00	.01	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:sample:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.01	.01	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:sample:linear:balance	.00	.00	.00	.00	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01	.00	.01	.01	.01	.01

fct:responses:sample:linear:f_cor	.01	.00	.00	.00	.02	.02	.02	.02	.01	.00	.02	.02	.02	.02	.00	.02	.02	.02	.02
fct:responses:sample:linear:items	.00	.00	.00	.01	.00	.00	.00	.00	.00	.01	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:sample:linear:loading	.01	.01	.01	.01	.02	.02	.02	.02	.01	.01	.02	.02	.02	.02	.01	.02	.02	.02	.02
fct:responses:sample:loading:balance	.01	.01	.01	.01	.02	.02	.02	.02	.01	.01	.02	.02	.02	.02	.01	.02	.02	.02	.02
fct:responses:sample:loading:f_cor	.01	.02	.02	.01	.03	.03	.03	.03	.02	.01	.03	.03	.03	.03	.01	.03	.03	.03	.03
fct:responses:sample:loading:items	.01	.01	.01	.01	.00	.00	.00	.00	.01	.01	.00	.00	.00	.00	.01	.00	.00	.00	.00
fct:sample:items:balance:f_cor	.00	.00	.00	.00	.01	.01	.01	.01	.01	.00	.01	.01	.01	.01	.00	.01	.01	.01	.01
fct:sample:linear:balance:f_cor	.00	.01	.01	.00	.01	.01	.01	.01	.00	.00	.01	.01	.01	.01	.00	.01	.01	.01	.01
fct:sample:linear:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:sample:linear:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:sample:linear:loading:balance	.01	.00	.00	.00	.01	.01	.01	.01	.00	.00	.01	.01	.01	.01	.00	.01	.01	.01	.01
fct:sample:linear:loading:f_cor	.01	.01	.00	.00	.02	.02	.02	.02	.01	.00	.02	.02	.02	.02	.00	.02	.02	.02	.02
fct:sample:linear:loading:items	.00	.00	.00	.00	.00	.00	.00	.00	.01	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:sample:loading:balance:f_cor	.00	.00	.01	.00	.02	.02	.02	.02	.00	.00	.02	.02	.02	.02	.00	.02	.02	.02	.02
fct:sample:loading:items:balance	.01	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:sample:loading:items:f_cor	.00	.01	.00	.02	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
linear:loading:items:balance:f_cor	.00	.00	.00	.00	.01	.01	.01	.01	.00	.00	.01	.01	.01	.01	.00	.01	.01	.01	.01
responses:linear:items:balance:f_cor	.00	.00	.00	.00	.01	.01	.01	.01	.00	.00	.01	.01	.01	.01	.00	.01	.01	.01	.01
responses:linear:loading:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:linear:loading:items:balance	.00	.00	.00	.00	.01	.01	.01	.01	.00	.00	.01	.01	.01	.01	.00	.01	.01	.01	.01
responses:linear:loading:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:loading:items:balance:f_cor	.00	.00	.00	.00	.01	.01	.01	.01	.00	.00	.01	.01	.01	.01	.00	.01	.01	.01	.01
responses:sample:items:balance:f_cor	.00	.00	.00	.00	.02	.02	.02	.02	.00	.00	.02	.02	.02	.02	.00	.02	.02	.02	.02
responses:sample:linear:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:linear:items:balance	.00	.00	.00	.00	.01	.01	.01	.01	.00	.00	.01	.01	.01	.01	.00	.01	.01	.01	.01
responses:sample:linear:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:linear:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.01	.01	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:linear:loading:f_cor	.00	.01	.01	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:linear:loading:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:loading:balance:f_cor	.00	.00	.00	.01	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:loading:items:balance	.00	.00	.00	.00	.02	.02	.02	.02	.00	.00	.02	.02	.02	.02	.00	.02	.02	.02	.02
responses:sample:loading:items:f_cor	.00	.00	.00	.01	.00	.00	.00	.00	.01	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:linear:items:balance:f_cor	.00	.00	.00	.00	.01	.01	.01	.01	.00	.00	.01	.01	.01	.01	.00	.01	.01	.01	.01
sample:linear:loading:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:linear:loading:items:balance	.00	.00	.00	.00	.02	.02	.02	.02	.00	.00	.02	.02	.02	.02	.00	.02	.02	.02	.02
sample:linear:loading:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:loading:items:balance:f_cor	.00	.00	.00	.00	.02	.02	.02	.02	.00	.00	.02	.02	.02	.02	.00	.02	.02	.02	.02
fct:linear:loading:items:balance:f_cor	.00	.00	.00	.00	.01	.01	.01	.01	.00	.00	.01	.01	.01	.01	.00	.01	.01	.01	.01
fct:responses:linear:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:linear:loading:balance:f_cor	.00	.00	.00	.00	.02	.02	.02	.02	.00	.00	.02	.02	.02	.02	.00	.02	.02	.02	.02
fct:responses:linear:loading:items:balance	.00	.00	.00	.00	.01	.01	.01	.01	.00	.00	.01	.01	.01	.01	.00	.01	.01	.01	.01
fct:responses:linear:loading:items:f_cor	.00	.01	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:loading:items:balance:f_cor	.00	.00	.00	.00	.01	.01	.01	.01	.00	.00	.01	.01	.01	.01	.00	.01	.01	.01	.01
fct:responses:sample:items:balance:f_cor	.01	.01	.01	.00	.02	.02	.02	.02	.01	.00	.02	.02	.02	.02	.00	.02	.02	.02	.02
fct:responses:sample:linear:balance:f_cor	.01	.01	.00	.00	.03	.03	.03	.03	.00	.00	.03	.03	.03	.03	.00	.03	.03	.03	.03
fct:responses:sample:linear:items:balance	.01	.00	.00	.00	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01	.00	.01	.01	.01	.01
fct:responses:sample:linear:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.01	.01	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:sample:linear:loading:balance	.01	.01	.01	.01	.03	.03	.03	.03	.01	.01	.03	.03	.03	.03	.00	.03	.03	.03	.03
fct:responses:sample:linear:loading:f_cor	.01	.01	.01	.01	.05	.05	.05	.05	.01	.01	.05	.05	.05	.05	.00	.05	.05	.05	.05
fct:responses:sample:linear:loading:items	.01	.01	.01	.01	.00	.00	.00	.00	.01	.01	.00	.00	.00	.00	.01	.00	.00	.00	.00
fct:responses:sample:loading:balance:f_cor	.00	.01	.01	.01	.05	.05	.05	.05	.01	.01	.05	.05	.05	.05	.01	.05	.05	.05	.05
fct:responses:sample:loading:items:balance	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01
fct:responses:sample:loading:items:f_cor	.01	.01	.01	.01	.00	.00	.00	.00	.01	.01	.00	.00	.00	.00	.01	.00	.00	.00	.00
fct:sample:linear:items:balance:f_cor	.00	.00	.00	.00	.01	.01	.01	.01	.00	.00	.01	.01	.01	.01	.00	.01	.01	.01	.01
fct:sample:linear:loading:balance:f_cor	.00	.01	.01	.00	.04	.04	.04	.04	.00	.00	.04	.04	.04	.04	.00	.04	.04	.04	.04
fct:sample:linear:loading:items:balance	.00	.01	.01	.01	.01	.01	.01	.01	.00	.00	.01	.01	.01	.01	.00	.01	.01	.01	.01
fct:sample:linear:loading:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.01	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:sample:loading:items:balance:f_cor	.00	.00	.00	.00	.02	.02	.02	.02	.01	.01	.02	.02	.02	.02	.00	.02	.02	.02	.02

responses:linear:loading:items:balance:f_cor	.00	.00	.00	.00	.02	.02	.02	.02	.00	.00	.02	.02	.02	.02	.00	.02	.02	.02	.02
responses:sample:linear:items:balance:f_cor	.00	.00	.00	.00	.02	.02	.02	.02	.00	.00	.02	.02	.02	.02	.00	.02	.02	.02	.02
responses:sample:linear:loading:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.01	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:linear:loading:items:balance	.01	.00	.00	.01	.03	.03	.03	.03	.00	.00	.03	.03	.03	.03	.00	.03	.03	.03	.03
responses:sample:linear:loading:items:f_cor	.01	.00	.00	.01	.01	.01	.01	.01	.00	.00	.01	.01	.01	.01	.00	.01	.01	.01	.01
responses:sample:loading:items:balance:f_cor	.00	.00	.00	.00	.04	.04	.04	.04	.00	.00	.04	.04	.04	.04	.00	.04	.04	.04	.04
sample:linear:loading:items:balance:f_cor	.00	.00	.00	.00	.03	.03	.03	.03	.00	.00	.03	.03	.03	.03	.00	.03	.03	.03	.03
fct:responses:linear:loading:items:balance:f_cor	.00	.00	.00	.00	.01	.01	.01	.01	.01	.00	.01	.01	.01	.01	.00	.01	.01	.01	.01
fct:responses:sample:linear:items:balance:f_cor	.00	.01	.01	.00	.02	.02	.02	.02	.01	.00	.02	.02	.02	.02	.00	.02	.02	.02	.02
fct:responses:sample:linear:loading:balance:f_cor	.01	.01	.01	.01	.07	.07	.07	.07	.01	.01	.07	.07	.07	.07	.01	.07	.07	.07	.07
fct:responses:sample:linear:loading:items:balance	.02	.01	.01	.01	.02	.02	.02	.02	.01	.01	.02	.02	.02	.02	.01	.02	.02	.02	.02
fct:responses:sample:linear:loading:items:f_cor	.01	.01	.01	.01	.00	.00	.00	.00	.01	.01	.00	.00	.00	.00	.01	.00	.00	.00	.00
fct:responses:sample:loading:items:balance:f_cor	.01	.01	.01	.01	.03	.03	.03	.03	.01	.01	.03	.03	.03	.03	.01	.03	.03	.03	.03
fct:sample:linear:loading:items:balance:f_cor	.00	.00	.00	.01	.02	.02	.02	.02	.01	.00	.02	.02	.02	.02	.00	.02	.02	.02	.02
responses:sample:linear:loading:items:balance:f_cor	.00	.00	.01	.00	.04	.04	.04	.04	.00	.00	.04	.04	.04	.04	.00	.04	.04	.04	.04
fct:responses:sample:linear:loading:items:balance:f_cor	.01	.01	.01	.01	.04	.04	.04	.04	.01	.01	.04	.04	.04	.04	.01	.04	.04	.04	.04

Table 43. MBE Partial Eta Squared by Term Interaction (Part 1)

Term	walktrap_atan_bic	louvain_atan_bic	leiden_atan_bic	walktrap_atan_gic_3	louvain_atan_gic_3	leiden_atan_gic_3	walktrap_atan_gic_4	louvain_atan_gic_4	leiden_atan_gic_4	walktrap_atan_ebic	louvain_atan_ebic	leiden_atan_ebic
balance	.00	.00	.01	.00	.00	.00	.00	.00	.01	.00	.00	.01
f_cor	.01	.00	.00	.01	.00	.00	.00	.00	.00	.00	.00	.00
fct	.13	.27	.27	.09	.22	.23	.03	.16	.16	.02	.11	.11
items	.12	.20	.20	.17	.24	.23	.22	.26	.26	.25	.25	.26
linear	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
loading	.06	.06	.06	.08	.07	.07	.11	.09	.10	.10	.07	.07
responses	.02	.00	.00	.01	.00	.00	.00	.01	.01	.00	.00	.00
sample	.03	.07	.06	.08	.11	.10	.11	.11	.11	.08	.06	.06
balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:balance	.00	.01	.01	.00	.01	.00	.00	.00	.00	.01	.01	.01
fct:f_cor	.03	.06	.06	.02	.05	.05	.01	.04	.04	.00	.02	.02
fct:items	.01	.01	.01	.02	.02	.02	.05	.02	.02	.04	.02	.02
fct:linear	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:loading	.01	.08	.08	.01	.06	.06	.00	.05	.05	.00	.04	.04
fct:responses	.07	.09	.08	.04	.06	.06	.01	.03	.02	.00	.01	.01
fct:sample	.03	.07	.06	.01	.04	.05	.01	.02	.02	.00	.02	.02
items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
items:f_cor	.02	.04	.04	.04	.05	.04	.03	.04	.03	.03	.02	.02
linear:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
linear:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
linear:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
linear:loading	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
loading:balance	.00	.01	.01	.00	.01	.01	.00	.00	.00	.00	.00	.00
loading:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.01	.00	.00
loading:items	.11	.13	.12	.14	.15	.14	.18	.19	.19	.23	.23	.24
responses:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:items	.00	.01	.01	.00	.02	.02	.01	.02	.01	.01	.01	.01
responses:linear	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:loading	.01	.01	.01	.01	.01	.01	.00	.00	.00	.00	.00	.00

responses:sample	.02	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:f_cor	.00	.00	.00	.00	.00	.00	.01	.00	.00	.02	.01	.01
sample:items	.05	.09	.09	.09	.12	.12	.13	.15	.16	.12	.12	.12
sample:linear	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:loading	.11	.08	.08	.16	.11	.11	.12	.09	.09	.06	.04	.04
fct:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:items:f_cor	.01	.01	.01	.01	.01	.01	.01	.00	.00	.01	.00	.00
fct:linear:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:linear:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:linear:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:linear:loading	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:loading:f_cor	.01	.01	.02	.00	.01	.01	.00	.01	.01	.00	.01	.01
fct:loading:items	.01	.00	.00	.02	.01	.01	.04	.02	.02	.04	.02	.02
fct:responses:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:items	.01	.01	.01	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:linear	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:loading	.00	.00	.00	.01	.01	.00	.00	.00	.00	.00	.00	.00
fct:responses:sample	.04	.03	.04	.02	.02	.02	.01	.01	.01	.01	.01	.01
fct:sample:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:sample:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:sample:items	.00	.00	.00	.01	.00	.00	.01	.00	.00	.01	.00	.00
fct:sample:linear	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:sample:loading	.02	.02	.02	.02	.02	.02	.02	.02	.02	.01	.01	.01
items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
linear:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
linear:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
linear:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
linear:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
linear:loading:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
linear:loading:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
loading:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
loading:items:f_cor	.01	.01	.01	.01	.01	.01	.01	.01	.00	.01	.00	.00
responses:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:linear:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:linear:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:linear:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:linear:loading	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:loading:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:loading:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:balance	.00	.00	.00	.00	.01	.01	.00	.00	.00	.00	.00	.00
responses:sample:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:items	.01	.00	.00	.00	.01	.00	.00	.00	.00	.00	.00	.00
responses:sample:linear	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:loading	.01	.01	.01	.01	.01	.01	.01	.01	.01	.04	.03	.04
sample:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:linear:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:linear:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:linear:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00

sample:linear:loading	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:loading:balance	.00	.00	.00	.00	.00	.01	.00	.00	.00	.00	.00	.00
sample:loading:f_cor	.00	.00	.00	.01	.01	.00	.01	.01	.01	.01	.00	.00
sample:loading:items	.04	.03	.03	.06	.04	.04	.09	.08	.08	.08	.07	.08
fct:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:linear:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:linear:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:linear:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:linear:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:linear:loading:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:linear:loading:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:loading:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:loading:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:items:balance	.00	.00	.00	.01	.00	.00	.01	.00	.00	.00	.00	.00
fct:responses:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:linear:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:linear:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:linear:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:linear:loading	.00	.01	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:loading:balance	.00	.01	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:loading:f_cor	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01
fct:responses:loading:items	.00	.00	.00	.00	.00	.00	.00	.00	.01	.00	.00	.00
fct:responses:sample:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.01	.00	.00
fct:responses:sample:f_cor	.00	.01	.01	.00	.01	.01	.00	.01	.01	.01	.01	.01
fct:responses:sample:items	.01	.00	.01	.01	.01	.01	.00	.00	.00	.01	.01	.01
fct:responses:sample:linear	.01	.01	.00	.01	.00	.00	.01	.00	.00	.00	.00	.00
fct:responses:sample:loading	.01	.02	.02	.02	.02	.01	.01	.02	.02	.01	.01	.01
fct:sample:balance:f_cor	.00	.00	.00	.01	.00	.00	.00	.00	.00	.00	.00	.00
fct:sample:items:balance	.01	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:sample:items:f_cor	.01	.00	.00	.01	.00	.00	.01	.01	.01	.00	.01	.01
fct:sample:linear:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:sample:linear:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:sample:linear:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:sample:linear:loading	.01	.01	.00	.01	.01	.01	.01	.00	.00	.01	.01	.01
fct:sample:loading:balance	.00	.01	.01	.00	.00	.00	.00	.00	.01	.00	.00	.00
fct:sample:loading:f_cor	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01	.02	.02
fct:sample:loading:items	.00	.01	.01	.01	.00	.00	.01	.01	.01	.01	.01	.01
linear:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
linear:loading:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
linear:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
linear:loading:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
loading:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:linear:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:linear:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:linear:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:linear:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:linear:loading:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:linear:loading:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:loading:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:loading:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:items:f_cor	.01	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:linear:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00

responses:sample:linear:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:linear:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:linear:loading	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:loading:balance	.00	.00	.00	.00	.01	.01	.00	.00	.00	.00	.00	.00
responses:sample:loading:f_cor	.01	.00	.00	.00	.00	.00	.01	.01	.01	.00	.01	.00
responses:sample:loading:items	.02	.02	.02	.01	.02	.03	.01	.03	.03	.02	.01	.01
sample:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:linear:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:linear:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:linear:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:linear:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:linear:loading:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:linear:loading:items	.00	.00	.00	.00	.01	.00	.00	.00	.00	.00	.00	.00
sample:loading:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.01	.00
sample:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:loading:items:f_cor	.00	.01	.01	.00	.01	.01	.01	.02	.02	.01	.02	.02
fct:linear:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:linear:loading:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:linear:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:linear:loading:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:loading:items:balance:f_cor	.00	.00	.00	.00	.01	.00	.00	.00	.00	.00	.00	.00
fct:responses:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:linear:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:linear:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:linear:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:linear:loading:balance	.00	.00	.01	.00	.00	.00	.01	.00	.01	.00	.00	.00
fct:responses:linear:loading:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:linear:loading:items	.01	.00	.00	.01	.00	.00	.00	.00	.00	.01	.00	.00
fct:responses:loading:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:loading:items:balance	.00	.00	.00	.01	.00	.00	.01	.00	.00	.00	.00	.00
fct:responses:loading:items:f_cor	.01	.00	.00	.01	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:sample:balance:f_cor	.00	.00	.00	.01	.01	.00	.01	.00	.00	.00	.00	.00
fct:responses:sample:items:balance	.01	.00	.00	.01	.00	.00	.01	.00	.00	.00	.00	.00
fct:responses:sample:items:f_cor	.01	.00	.00	.01	.01	.01	.00	.01	.01	.01	.01	.00
fct:responses:sample:linear:balance	.00	.01	.01	.00	.01	.01	.00	.01	.01	.01	.01	.00
fct:responses:sample:linear:f_cor	.00	.00	.00	.01	.01	.00	.01	.01	.01	.01	.01	.01
fct:responses:sample:linear:items	.00	.00	.00	.00	.01	.01	.00	.00	.00	.01	.00	.00
fct:responses:sample:linear:loading	.01	.02	.01	.01	.01	.01	.01	.00	.00	.01	.01	.01
fct:responses:sample:loading:balance	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01	.00	.00
fct:responses:sample:loading:f_cor	.01	.01	.01	.01	.01	.01	.02	.02	.02	.02	.02	.02
fct:responses:sample:loading:items	.01	.01	.01	.01	.01	.01	.01	.01	.01	.02	.01	.01
fct:sample:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:sample:linear:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:sample:linear:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:sample:linear:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:sample:linear:loading:balance	.00	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01
fct:sample:linear:loading:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.01	.00	.00
fct:sample:linear:loading:items	.00	.00	.00	.01	.00	.01	.00	.00	.00	.00	.01	.01
fct:sample:loading:balance:f_cor	.00	.01	.01	.01	.01	.01	.00	.00	.01	.00	.00	.00
fct:sample:loading:items:balance	.01	.00	.00	.01	.00	.00	.01	.00	.00	.01	.01	.01
fct:sample:loading:items:f_cor	.01	.01	.00	.01	.01	.01	.01	.02	.02	.01	.01	.01
linear:loading:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:linear:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:linear:loading:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:linear:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:linear:loading:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:loading:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00

responses:sample:linear:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:linear:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:linear:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.01	.01	.00	.01	.01
responses:sample:linear:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.01	.00	.00
responses:sample:linear:loading:f_cor	.00	.00	.00	.00	.00	.00	.01	.00	.00	.00	.00	.00
responses:sample:linear:loading:items	.00	.00	.00	.00	.00	.00	.01	.00	.00	.00	.00	.00
responses:sample:loading:balance:f_cor	.00	.01	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:loading:items:f_cor	.00	.01	.01	.00	.01	.01	.00	.01	.01	.00	.01	.01
sample:linear:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:linear:loading:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:linear:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:linear:loading:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.01	.00	.00
sample:loading:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:linear:loading:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:linear:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:linear:loading:balance:f_cor	.00	.00	.00	.00	.00	.00	.01	.00	.00	.00	.00	.00
fct:responses:linear:loading:items:balance	.00	.00	.00	.00	.01	.00	.01	.00	.00	.00	.00	.00
fct:responses:linear:loading:items:f_cor	.00	.00	.00	.01	.00	.00	.00	.00	.00	.00	.00	.01
fct:responses:loading:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:sample:items:balance:f_cor	.01	.00	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01
fct:responses:sample:linear:balance:f_cor	.01	.01	.01	.01	.01	.01	.00	.00	.00	.00	.00	.00
fct:responses:sample:linear:items:balance	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01
fct:responses:sample:linear:items:f_cor	.01	.00	.01	.01	.01	.01	.01	.01	.01	.01	.00	.00
fct:responses:sample:linear:loading:balance	.01	.01	.01	.01	.01	.01	.01	.01	.01	.02	.02	.02
fct:responses:sample:linear:loading:f_cor	.01	.01	.01	.01	.01	.01	.02	.01	.01	.02	.01	.01
fct:responses:sample:linear:loading:items	.01	.01	.01	.01	.01	.01	.01	.01	.01	.02	.01	.02
fct:responses:sample:loading:balance:f_cor	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01
fct:responses:sample:loading:items:balance	.01	.01	.01	.01	.01	.01	.02	.01	.01	.01	.01	.02
fct:responses:sample:loading:items:f_cor	.01	.01	.01	.02	.01	.01	.01	.02	.02	.02	.02	.02
fct:sample:linear:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:sample:linear:loading:balance:f_cor	.01	.01	.00	.01	.00	.01	.00	.00	.00	.00	.00	.00
fct:sample:linear:loading:items:balance	.01	.00	.00	.00	.00	.00	.00	.01	.00	.01	.00	.00
fct:sample:linear:loading:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.01	.00	.00
fct:sample:loading:items:balance:f_cor	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01
responses:linear:loading:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:linear:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:linear:loading:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:linear:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:linear:loading:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.01	.01	.01	.01
responses:sample:loading:items:balance:f_cor	.00	.01	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:linear:loading:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:linear:loading:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:sample:linear:items:balance:f_cor	.01	.01	.01	.01	.01	.01	.00	.00	.00	.01	.01	.01
fct:responses:sample:linear:loading:balance:f_cor	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01
fct:responses:sample:linear:loading:items:balance	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01
fct:responses:sample:linear:loading:items:f_cor	.01	.01	.01	.01	.01	.01	.01	.02	.02	.01	.01	.01
fct:responses:sample:loading:items:balance:f_cor	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01
fct:sample:linear:loading:items:balance:f_cor	.00	.01	.01	.00	.00	.01	.00	.01	.01	.01	.01	.00
responses:sample:linear:loading:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:sample:linear:loading:items:balance:f_cor	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01

Table 44. MBE Partial Eta Squared by Term Interaction (Part 2)

Term	walktrap_lasso_bic	louvain_lasso_bic	leiden_lasso_bic	walktrap_lasso_gic_3	louvain_lasso_gic_3	leiden_lasso_gic_3	walktrap_lasso_gic_4	louvain_lasso_gic_4	leiden_lasso_gic_4	walktrap_lasso_ebic	louvain_lasso_ebic	leiden_lasso_ebic
balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor	.11	.02	.02	.11	.03	.03	.10	.03	.04	.08	.04	.05
fct	.23	.30	.31	.20	.30	.31	.15	.22	.22	.18	.20	.20
items	.08	.16	.17	.11	.17	.17	.09	.08	.08	.05	.03	.03
linear	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
loading	.01	.00	.00	.01	.00	.00	.06	.05	.06	.22	.23	.23
responses	.12	.00	.00	.06	.00	.00	.00	.03	.03	.03	.06	.06
sample	.02	.00	.00	.01	.00	.00	.07	.07	.06	.19	.21	.21
balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:balance	.00	.00	.01	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor	.07	.06	.06	.07	.07	.07	.06	.06	.06	.05	.05	.05
fct:items	.02	.02	.02	.04	.03	.02	.03	.02	.02	.01	.01	.01
fct:linear	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:loading	.02	.07	.07	.02	.09	.08	.06	.10	.10	.10	.12	.12
fct:responses	.11	.13	.12	.05	.07	.07	.01	.01	.01	.00	.00	.00
fct:sample	.03	.08	.08	.02	.09	.10	.05	.09	.09	.08	.09	.09
items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
items:f_cor	.03	.03	.03	.03	.03	.02	.02	.01	.01	.01	.00	.00
linear:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
linear:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
linear:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
linear:loading	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
loading:f_cor	.04	.00	.00	.05	.01	.01	.04	.01	.01	.03	.02	.02
loading:items	.06	.09	.09	.06	.08	.08	.03	.03	.03	.02	.02	.02
responses:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:items	.00	.02	.02	.01	.04	.04	.01	.02	.01	.02	.02	.01
responses:linear	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:loading	.02	.02	.03	.05	.05	.05	.05	.06	.06	.06	.07	.07
responses:sample	.05	.01	.01	.01	.01	.01	.01	.03	.03	.03	.04	.04
sample:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:f_cor	.00	.00	.00	.00	.01	.01	.00	.01	.01	.00	.01	.01
sample:items	.02	.06	.06	.02	.05	.05	.01	.01	.01	.00	.00	.00
sample:linear	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:loading	.08	.04	.04	.06	.03	.02	.02	.07	.07	.13	.19	.18
fct:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:items:f_cor	.01	.01	.01	.01	.01	.00	.01	.00	.00	.00	.00	.00
fct:linear:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:linear:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:linear:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:linear:loading	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:loading:f_cor	.02	.02	.02	.03	.03	.03	.02	.02	.02	.02	.02	.02
fct:loading:items	.02	.01	.02	.02	.02	.02	.01	.00	.01	.00	.00	.00
fct:responses:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:items	.00	.01	.01	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:linear	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00

fct:responses:loading	.01	.01	.01	.03	.02	.03	.01	.01	.01	.01	.01	.01
fct:responses:sample	.04	.06	.06	.02	.02	.02	.01	.01	.01	.01	.00	.00
fct:sample:balance	.00	.00	.00	.00	.01	.01	.00	.00	.00	.00	.00	.00
fct:sample:f_cor	.01	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:sample:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:sample:linear	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:sample:loading	.02	.01	.01	.02	.01	.01	.02	.02	.02	.04	.04	.04
items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
linear:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
linear:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
linear:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
linear:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
linear:loading:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
linear:loading:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
loading:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
loading:items:f_cor	.01	.01	.01	.01	.00	.00	.00	.00	.00	.00	.00	.00
responses:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:linear:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:linear:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:linear:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:linear:loading	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:loading:f_cor	.00	.00	.01	.00	.00	.01	.00	.00	.00	.00	.01	.01
responses:loading:items	.00	.00	.00	.01	.00	.00	.00	.00	.00	.00	.01	.01
responses:sample:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:f_cor	.00	.00	.00	.00	.01	.00	.00	.00	.00	.00	.00	.00
responses:sample:items	.01	.01	.01	.00	.01	.01	.00	.01	.01	.01	.01	.01
responses:sample:linear	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:loading	.02	.01	.01	.07	.04	.04	.09	.06	.06	.05	.04	.04
sample:balance:f_cor	.00	.00	.00	.00	.00	.01	.00	.00	.00	.00	.00	.00
sample:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:linear:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:linear:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:linear:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:linear:loading	.00	.00	.00	.00	.01	.00	.00	.00	.00	.00	.00	.00
sample:loading:balance	.00	.00	.01	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:loading:f_cor	.01	.00	.00	.00	.01	.01	.00	.00	.00	.01	.00	.00
sample:loading:items	.02	.03	.02	.01	.01	.01	.00	.00	.00	.01	.01	.01
fct:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:linear:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:linear:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:linear:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:linear:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.01	.01	.01
fct:linear:loading:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:linear:loading:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:loading:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:loading:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.01	.01	.01
fct:responses:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:linear:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:linear:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:linear:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00

fct:responses:linear:loading	.00	.00	.00	.01	.01	.01	.00	.00	.00	.00	.00	.00
fct:responses:loading:balance	.00	.00	.01	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:loading:f_cor	.00	.00	.00	.00	.01	.01	.01	.00	.00	.00	.00	.00
fct:responses:loading:items	.00	.00	.00	.01	.00	.01	.00	.00	.00	.00	.01	.01
fct:responses:sample:balance	.00	.00	.00	.00	.00	.00	.00	.00	.01	.00	.00	.00
fct:responses:sample:f_cor	.01	.01	.01	.01	.01	.01	.00	.00	.00	.01	.00	.00
fct:responses:sample:items	.01	.02	.01	.00	.01	.00	.00	.00	.01	.00	.00	.00
fct:responses:sample:linear	.00	.00	.00	.00	.00	.00	.01	.01	.01	.00	.00	.00
fct:responses:sample:loading	.02	.02	.03	.05	.06	.07	.03	.03	.03	.03	.02	.03
fct:sample:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:sample:items:balance	.00	.00	.00	.01	.01	.00	.00	.00	.00	.00	.00	.00
fct:sample:items:f_cor	.01	.00	.00	.00	.00	.01	.00	.00	.00	.00	.00	.00
fct:sample:linear:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:sample:linear:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:sample:linear:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:sample:linear:loading	.01	.01	.01	.00	.01	.01	.00	.00	.01	.00	.00	.00
fct:sample:loading:balance	.00	.00	.00	.00	.01	.01	.00	.00	.00	.00	.00	.00
fct:sample:loading:f_cor	.01	.01	.01	.00	.01	.01	.01	.01	.01	.01	.01	.01
fct:sample:loading:items	.00	.01	.01	.00	.01	.01	.01	.00	.00	.01	.01	.01
linear:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
linear:loading:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
linear:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
linear:loading:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
loading:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:linear:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:linear:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:linear:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:linear:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:linear:loading:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:linear:loading:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:loading:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:loading:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:linear:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:linear:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:linear:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:linear:loading	.00	.00	.00	.00	.00	.00	.01	.00	.00	.00	.00	.00
responses:sample:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:loading:f_cor	.00	.00	.00	.01	.01	.01	.00	.01	.01	.00	.00	.00
responses:sample:loading:items	.02	.02	.03	.00	.00	.00	.01	.01	.01	.01	.01	.01
sample:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:linear:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:linear:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:linear:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:linear:loading:balance	.00	.01	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:linear:loading:f_cor	.00	.01	.01	.00	.00	.00	.00	.00	.00	.01	.01	.01
sample:linear:loading:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:loading:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:loading:items:f_cor	.00	.00	.00	.01	.01	.01	.01	.01	.01	.01	.00	.00
fct:linear:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:linear:loading:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:linear:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:linear:loading:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00

fct:loading:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:linear:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:linear:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:linear:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:linear:loading:balance	.00	.00	.00	.01	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:linear:loading:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:linear:loading:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:loading:balance:f_cor	.01	.00	.00	.00	.00	.00	.00	.00	.00	.01	.01	.01
fct:responses:loading:items:balance	.00	.00	.00	.01	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:loading:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.01	.01
fct:responses:sample:balance:f_cor	.01	.00	.01	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:sample:items:balance	.00	.00	.00	.01	.01	.00	.00	.00	.00	.00	.01	.01
fct:responses:sample:items:f_cor	.01	.01	.01	.00	.00	.00	.00	.00	.00	.01	.01	.01
fct:responses:sample:linear:balance	.01	.00	.00	.00	.00	.01	.00	.00	.00	.00	.01	.00
fct:responses:sample:linear:f_cor	.00	.01	.01	.01	.01	.01	.00	.00	.00	.00	.00	.00
fct:responses:sample:linear:items	.01	.01	.00	.01	.00	.00	.01	.01	.00	.00	.00	.00
fct:responses:sample:linear:loading	.01	.01	.01	.01	.02	.01	.02	.01	.01	.02	.02	.02
fct:responses:sample:loading:balance	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01
fct:responses:sample:loading:f_cor	.01	.01	.01	.01	.01	.02	.01	.01	.01	.02	.02	.02
fct:responses:sample:loading:items	.02	.02	.02	.01	.01	.02	.01	.01	.01	.01	.01	.01
fct:sample:items:balance:f_cor	.00	.00	.00	.01	.01	.01	.00	.00	.00	.00	.00	.00
fct:sample:linear:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:sample:linear:items:balance	.00	.00	.00	.00	.01	.01	.00	.00	.00	.00	.00	.00
fct:sample:linear:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.01	.01
fct:sample:linear:loading:balance	.00	.01	.01	.00	.01	.00	.00	.01	.00	.00	.00	.00
fct:sample:linear:loading:f_cor	.00	.01	.01	.00	.01	.01	.01	.01	.00	.01	.01	.01
fct:sample:linear:loading:items	.00	.00	.00	.00	.01	.01	.00	.00	.00	.00	.00	.00
fct:sample:loading:balance:f_cor	.01	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:sample:loading:items:balance	.01	.00	.01	.01	.01	.01	.01	.00	.00	.00	.00	.00
fct:sample:loading:items:f_cor	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01
linear:loading:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:linear:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:linear:loading:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:linear:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:linear:loading:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:loading:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:linear:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:linear:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:linear:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:linear:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:linear:loading:f_cor	.00	.00	.01	.00	.01	.01	.00	.00	.00	.00	.00	.00
responses:sample:linear:loading:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:loading:balance:f_cor	.00	.00	.00	.00	.01	.01	.00	.00	.00	.00	.00	.00
responses:sample:loading:items:balance	.00	.00	.01	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:loading:items:f_cor	.00	.01	.00	.00	.00	.00	.00	.00	.00	.01	.01	.01
sample:linear:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:linear:loading:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:linear:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:linear:loading:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:loading:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:linear:loading:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:linear:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:linear:loading:balance:f_cor	.01	.00	.00	.01	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:linear:loading:items:balance	.00	.00	.00	.01	.01	.01	.00	.00	.00	.00	.00	.00
fct:responses:linear:loading:items:f_cor	.00	.00	.01	.01	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:loading:items:balance:f_cor	.00	.00	.00	.00	.01	.01	.00	.00	.00	.00	.00	.00

fct:responses:sample:items:balance:f_cor	.01	.01	.01	.00	.01	.01	.01	.01	.01	.01	.01	.01
fct:responses:sample:linear:balance:f_cor	.00	.01	.01	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:sample:linear:items:balance	.01	.01	.00	.01	.01	.01	.00	.01	.01	.01	.00	.00
fct:responses:sample:linear:items:f_cor	.01	.01	.01	.01	.01	.01	.00	.00	.00	.01	.01	.01
fct:responses:sample:linear:loading:balance	.01	.01	.01	.01	.00	.01	.01	.01	.01	.01	.01	.01
fct:responses:sample:linear:loading:f_cor	.01	.01	.01	.02	.02	.01	.01	.01	.01	.01	.01	.01
fct:responses:sample:linear:loading:items	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01
fct:responses:sample:loading:balance:f_cor	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01
fct:responses:sample:loading:items:balance	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01
fct:responses:sample:loading:items:f_cor	.01	.02	.02	.01	.01	.01	.01	.01	.01	.01	.02	.02
fct:sample:linear:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:sample:linear:loading:balance:f_cor	.01	.01	.00	.01	.01	.01	.00	.00	.00	.00	.01	.00
fct:sample:linear:loading:items:balance	.00	.00	.00	.01	.01	.01	.01	.00	.00	.00	.01	.00
fct:sample:linear:loading:items:f_cor	.00	.01	.01	.00	.01	.01	.01	.01	.01	.01	.01	.01
fct:sample:loading:items:balance:f_cor	.00	.00	.00	.00	.01	.01	.00	.00	.01	.00	.00	.00
responses:linear:loading:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:linear:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:linear:loading:balance:f_cor	.00	.00	.00	.00	.00	.01	.00	.00	.00	.00	.00	.00
responses:sample:linear:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.01	.01	.01
responses:sample:linear:loading:items:f_cor	.00	.01	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:loading:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:linear:loading:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:linear:loading:items:balance:f_cor	.00	.00	.01	.00	.00	.00	.01	.00	.01	.00	.00	.00
fct:responses:sample:linear:items:balance:f_cor	.00	.00	.00	.01	.01	.01	.00	.01	.00	.01	.01	.01
fct:responses:sample:linear:loading:balance:f_cor	.01	.02	.02	.01	.01	.01	.01	.01	.01	.01	.01	.01
fct:responses:sample:linear:loading:items:balance	.01	.01	.02	.01	.01	.01	.01	.02	.02	.01	.01	.01
fct:responses:sample:linear:loading:items:f_cor	.02	.02	.02	.01	.02	.02	.01	.01	.01	.01	.01	.01
fct:responses:sample:loading:items:balance:f_cor	.01	.01	.02	.01	.02	.02	.01	.01	.01	.01	.01	.01
fct:sample:linear:loading:items:balance:f_cor	.01	.01	.01	.01	.00	.00	.01	.00	.00	.00	.00	.01
responses:sample:linear:loading:items:balance:f_cor	.00	.00	.00	.00	.01	.00	.00	.01	.01	.00	.00	.00
fct:responses:sample:linear:loading:items:balance:f_cor	.01	.01	.01	.01	.01	.01	.01	.01	.02	.01	.01	.01

Table 45. MBE Partial Eta Squared by Term Interaction (Part 3)

Term	**walktrap_adapt_bic**	**louvain_adapt_bic**	**leiden_adapt_bic**	**walktrap_adapt_gic_3**	**louvain_adapt_gic_3**	**leiden_adapt_gic_3**	**walktrap_adapt_gic_4**	**louvain_adapt_gic_4**	**leiden_adapt_gic_4**	**walktrap_adapt_ebic**	**louvain_adapt_ebic**	**leiden_adapt_ebic**
balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor	.03	.00	.01	.03	.00	.00	.01	.00	.00	.00	.00	.00
fct	.12	.21	.22	.12	.22	.21	.11	.19	.18	.12	.17	.17
items	.11	.18	.17	.11	.13	.13	.08	.07	.07	.07	.06	.06
linear	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
loading	.01	.01	.01	.00	.00	.00	.05	.08	.08	.30	.35	.35
responses	.02	.01	.01	.00	.02	.02	.02	.05	.05	.03	.05	.05
sample	.00	.02	.02	.01	.01	.01	.07	.09	.09	.18	.21	.21
balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:balance	.00	.01	.01	.00	.01	.01	.01	.01	.01	.00	.00	.00
fct:f_cor	.03	.04	.05	.03	.03	.03	.02	.02	.02	.01	.01	.01
fct:items	.02	.02	.02	.03	.02	.02	.02	.01	.02	.01	.01	.01
fct:linear	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:loading	.02	.07	.07	.04	.10	.10	.08	.14	.13	.12	.17	.16
fct:responses	.05	.04	.05	.02	.03	.02	.00	.00	.00	.00	.00	.00
fct:sample	.02	.05	.06	.04	.09	.09	.07	.11	.11	.06	.08	.08

items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
items:f_cor	.03	.03	.02	.03	.03	.02	.02	.02	.01	.02	.01	.01
linear:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
linear:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
linear:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
linear:loading	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
loading:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
loading:items	.10	.11	.12	.08	.07	.07	.04	.03	.03	.04	.04	.04
responses:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:f_cor	.01	.00	.00	.01	.00	.00	.00	.00	.00	.00	.00	.00
responses:items	.00	.02	.01	.01	.02	.02	.01	.02	.02	.01	.01	.01
responses:linear	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:loading	.02	.02	.02	.03	.03	.03	.06	.06	.07	.06	.06	.07
responses:sample	.01	.01	.01	.00	.02	.03	.05	.06	.07	.03	.02	.02
sample:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:items	.04	.09	.09	.03	.05	.05	.01	.01	.01	.01	.01	.01
sample:linear	.00	.00	.01	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:loading	.09	.03	.04	.05	.01	.01	.14	.21	.20	.32	.37	.37
fct:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:items:f_cor	.02	.01	.01	.02	.01	.01	.01	.00	.00	.00	.00	.00
fct:linear:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:linear:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:linear:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:linear:loading	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:loading:balance	.00	.00	.00	.00	.00	.00	.01	.01	.01	.00	.00	.00
fct:loading:f_cor	.00	.01	.01	.00	.01	.01	.00	.01	.01	.00	.00	.01
fct:loading:items	.01	.01	.01	.02	.01	.01	.01	.01	.01	.00	.00	.00
fct:responses:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:f_cor	.00	.00	.00	.01	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:linear	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:loading	.00	.01	.00	.01	.01	.01	.01	.01	.01	.01	.01	.01
fct:responses:sample	.03	.02	.03	.01	.01	.01	.00	.00	.00	.01	.02	.02
fct:sample:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:sample:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:sample:items	.00	.00	.00	.00	.00	.00	.01	.00	.01	.00	.00	.00
fct:sample:linear	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:sample:loading	.01	.01	.01	.02	.02	.03	.07	.08	.08	.08	.07	.07
items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
linear:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
linear:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
linear:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
linear:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
linear:loading:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
linear:loading:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
loading:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
loading:items:f_cor	.01	.01	.01	.01	.01	.00	.00	.00	.00	.00	.00	.00
responses:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:linear:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:linear:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:linear:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:linear:loading	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00

responses:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:loading:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.01	.01	.01
responses:loading:items	.00	.00	.00	.01	.00	.00	.01	.00	.00	.01	.00	.01
responses:sample:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.01	.01	.01
responses:sample:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:items	.01	.01	.01	.01	.01	.01	.01	.01	.01	.00	.00	.00
responses:sample:linear	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:loading	.02	.01	.01	.05	.02	.02	.08	.07	.07	.04	.03	.03
sample:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:linear:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:linear:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:linear:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:linear:loading	.00	.00	.01	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.01	.01
sample:loading:f_cor	.01	.01	.01	.02	.01	.01	.01	.00	.00	.01	.00	.00
sample:loading:items	.05	.03	.05	.02	.01	.01	.02	.02	.03	.02	.02	.02
fct:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:linear:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:linear:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:linear:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:linear:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.01
fct:linear:loading:f_cor	.00	.00	.00	.00	.00	.00	.00	.01	.01	.00	.00	.00
fct:linear:loading:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:loading:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:loading:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:linear:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:linear:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:linear:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:linear:loading	.00	.00	.00	.01	.01	.00	.00	.00	.00	.00	.01	.01
fct:responses:loading:balance	.00	.00	.00	.00	.00	.01	.00	.00	.00	.00	.00	.00
fct:responses:loading:f_cor	.01	.01	.01	.00	.01	.01	.01	.01	.01	.00	.00	.00
fct:responses:loading:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:sample:balance	.00	.00	.00	.00	.01	.01	.00	.00	.00	.00	.00	.00
fct:responses:sample:f_cor	.00	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01
fct:responses:sample:items	.01	.01	.01	.00	.00	.00	.00	.00	.00	.01	.01	.01
fct:responses:sample:linear	.00	.00	.00	.00	.01	.01	.00	.01	.01	.01	.01	.01
fct:responses:sample:loading	.02	.02	.02	.04	.05	.04	.02	.03	.03	.03	.03	.03
fct:sample:balance:f_cor	.00	.01	.01	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:sample:items:balance	.00	.00	.00	.00	.00	.00	.01	.01	.01	.00	.00	.00
fct:sample:items:f_cor	.00	.00	.00	.01	.01	.01	.00	.00	.00	.01	.00	.00
fct:sample:linear:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:sample:linear:f_cor	.00	.00	.00	.00	.00	.00	.00	.01	.01	.00	.00	.00
fct:sample:linear:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:sample:linear:loading	.01	.01	.01	.00	.01	.01	.00	.00	.01	.00	.00	.00
fct:sample:loading:balance	.01	.00	.00	.01	.00	.00	.01	.01	.00	.00	.00	.00
fct:sample:loading:f_cor	.02	.01	.01	.02	.01	.01	.01	.01	.01	.01	.01	.01
fct:sample:loading:items	.01	.01	.01	.00	.00	.00	.01	.01	.01	.01	.01	.01
linear:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
linear:loading:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
linear:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
linear:loading:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
loading:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00

responses:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:linear:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:linear:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:linear:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:linear:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:linear:loading:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:linear:loading:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:loading:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:loading:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:linear:balance	.00	.00	.00	.00	.00	.00	.00	.00	.01	.00	.00	.00
responses:sample:linear:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:linear:items	.00	.00	.00	.00	.00	.00	.01	.00	.00	.00	.00	.00
responses:sample:linear:loading	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.01	.01
responses:sample:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.01	.01	.01
responses:sample:loading:f_cor	.01	.00	.00	.01	.01	.00	.00	.01	.01	.01	.00	.00
responses:sample:loading:items	.01	.02	.02	.01	.01	.01	.01	.01	.01	.01	.00	.00
sample:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:linear:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:linear:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:linear:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:linear:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:linear:loading:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.01	.01	.01
sample:linear:loading:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.01	.01
sample:loading:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:loading:items:f_cor	.00	.01	.00	.00	.00	.00	.01	.01	.01	.01	.01	.01
fct:linear:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:linear:loading:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:linear:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:linear:loading:items:f_cor	.00	.00	.00	.00	.00	.00	.01	.01	.01	.00	.00	.00
fct:loading:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:linear:balance:f_cor	.00	.00	.00	.01	.01	.00	.00	.00	.00	.00	.00	.00
fct:responses:linear:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:linear:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:linear:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:linear:loading:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:linear:loading:items	.00	.01	.00	.00	.01	.01	.00	.01	.01	.00	.00	.00
fct:responses:loading:balance:f_cor	.01	.01	.01	.00	.00	.00	.00	.01	.00	.00	.00	.00
fct:responses:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:loading:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:sample:balance:f_cor	.00	.00	.00	.00	.00	.00	.01	.01	.01	.01	.00	.00
fct:responses:sample:items:balance	.00	.00	.00	.01	.00	.00	.01	.01	.01	.00	.00	.00
fct:responses:sample:items:f_cor	.00	.01	.01	.01	.01	.00	.00	.00	.00	.00	.00	.00
fct:responses:sample:linear:balance	.00	.00	.00	.01	.00	.01	.01	.00	.00	.00	.00	.00
fct:responses:sample:linear:f_cor	.00	.00	.00	.00	.01	.01	.00	.00	.00	.00	.00	.00
fct:responses:sample:linear:items	.00	.00	.00	.01	.01	.01	.01	.01	.01	.00	.01	.01
fct:responses:sample:linear:loading	.01	.01	.01	.01	.01	.01	.01	.01	.01	.02	.02	.02
fct:responses:sample:loading:balance	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01
fct:responses:sample:loading:f_cor	.01	.02	.01	.01	.01	.01	.02	.02	.02	.01	.02	.02
fct:responses:sample:loading:items	.01	.01	.01	.01	.01	.01	.01	.01	.01	.02	.01	.01
fct:sample:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.01	.00	.00	.01	.01	.01
fct:sample:linear:balance:f_cor	.00	.00	.00	.01	.00	.00	.00	.00	.00	.00	.00	.00
fct:sample:linear:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00

fct:sample:linear:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:sample:linear:loading:balance	.00	.01	.01	.00	.01	.00	.00	.00	.00	.00	.00	.00
fct:sample:linear:loading:f_cor	.00	.00	.00	.00	.00	.00	.01	.01	.01	.01	.00	.00
fct:sample:linear:loading:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:sample:loading:balance:f_cor	.01	.02	.02	.01	.01	.01	.00	.00	.01	.00	.00	.00
fct:sample:loading:items:balance	.01	.00	.00	.00	.00	.00	.01	.01	.01	.01	.01	.01
fct:sample:loading:items:f_cor	.01	.01	.01	.02	.01	.01	.01	.01	.00	.01	.01	.01
linear:loading:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:linear:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:linear:loading:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:linear:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:linear:loading:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:loading:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:linear:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:linear:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:linear:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:linear:loading:balance	.00	.00	.00	.00	.00	.00	.00	.01	.01	.00	.00	.00
responses:sample:linear:loading:f_cor	.00	.00	.00	.00	.01	.00	.00	.00	.00	.00	.00	.00
responses:sample:linear:loading:items	.00	.00	.00	.00	.00	.00	.01	.00	.00	.00	.01	.00
responses:sample:loading:balance:f_cor	.00	.01	.00	.00	.01	.01	.00	.00	.00	.00	.00	.00
responses:sample:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.01	.00	.00	.00	.00
responses:sample:loading:items:f_cor	.00	.01	.01	.01	.01	.01	.00	.01	.01	.00	.00	.00
sample:linear:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:linear:loading:balance:f_cor	.00	.00	.00	.00	.00	.01	.00	.00	.00	.00	.00	.00
sample:linear:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:linear:loading:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:loading:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.01	.00	.00
fct:linear:loading:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.01	.00	.01
fct:responses:linear:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.01	.00	.00	.00	.00	.00
fct:responses:linear:loading:balance:f_cor	.00	.00	.00	.01	.01	.01	.00	.00	.00	.01	.01	.01
fct:responses:linear:loading:items:balance	.00	.01	.01	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:linear:loading:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.01	.00	.00	.00	.00
fct:responses:loading:items:balance:f_cor	.00	.01	.01	.00	.00	.01	.00	.01	.01	.00	.00	.01
fct:responses:sample:items:balance:f_cor	.00	.00	.00	.01	.01	.01	.01	.01	.01	.01	.01	.01
fct:responses:sample:linear:balance:f_cor	.00	.01	.01	.01	.01	.01	.00	.00	.00	.00	.00	.01
fct:responses:sample:linear:items:balance	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01
fct:responses:sample:linear:items:f_cor	.01	.01	.01	.00	.01	.01	.01	.02	.01	.01	.01	.01
fct:responses:sample:linear:loading:balance	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01
fct:responses:sample:linear:loading:f_cor	.01	.01	.01	.01	.01	.01	.00	.01	.01	.01	.01	.01
fct:responses:sample:linear:loading:items	.01	.01	.01	.01	.02	.02	.01	.01	.01	.01	.01	.01
fct:responses:sample:loading:balance:f_cor	.01	.02	.02	.01	.01	.01	.01	.02	.02	.01	.01	.01
fct:responses:sample:loading:items:balance	.01	.01	.01	.00	.00	.01	.01	.01	.01	.01	.01	.01
fct:responses:sample:loading:items:f_cor	.01	.02	.01	.02	.01	.01	.01	.01	.01	.01	.01	.01
fct:sample:linear:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:sample:linear:loading:balance:f_cor	.00	.00	.00	.01	.00	.00	.00	.00	.01	.01	.00	.00
fct:sample:linear:loading:items:balance	.00	.00	.00	.00	.00	.00	.01	.00	.00	.01	.01	.01
fct:sample:linear:loading:items:f_cor	.00	.01	.01	.00	.00	.00	.01	.01	.01	.01	.00	.00
fct:sample:loading:items:balance:f_cor	.00	.00	.01	.00	.01	.01	.01	.01	.01	.01	.01	.01
responses:linear:loading:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:linear:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:linear:loading:balance:f_cor	.00	.00	.00	.00	.01	.01	.00	.00	.00	.00	.00	.00
responses:sample:linear:loading:items:balance	.00	.01	.01	.00	.01	.01	.00	.00	.00	.00	.00	.00
responses:sample:linear:loading:items:f_cor	.00	.00	.00	.00	.00	.01	.00	.00	.00	.00	.01	.01
responses:sample:loading:items:balance:f_cor	.00	.01	.00	.00	.00	.00	.00	.00	.00	.01	.01	.01
sample:linear:loading:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:linear:loading:items:balance:f_cor	.00	.00	.00	.00	.01	.00	.01	.00	.00	.00	.00	.00
fct:responses:sample:linear:items:balance:f_cor	.00	.00	.00	.01	.00	.01	.01	.01	.01	.01	.01	.01

fct:responses:sample:linear:loading:balance:f_cor	.01	.01	.01	.01	.02	.02	.00	.01	.01	.01	.01	.01
fct:responses:sample:linear:loading:items:balance	.01	.02	.02	.01	.02	.02	.01	.01	.01	.01	.01	.01
fct:responses:sample:linear:loading:items:f_cor	.01	.01	.01	.01	.01	.01	.02	.03	.03	.01	.01	.01
fct:responses:sample:loading:items:balance:f_cor	.01	.01	.01	.01	.02	.02	.01	.02	.02	.01	.02	.02
fct:sample:linear:loading:items:balance:f_cor	.01	.00	.01	.01	.01	.01	.01	.01	.01	.00	.00	.00
responses:sample:linear:loading:items:balance:f_cor	.00	.00	.00	.00	.01	.01	.00	.01	.01	.00	.00	.00
fct:responses:sample:linear:loading:items:balance:f_cor	.01	.01	.01	.01	.01	.01	.02	.02	.02	.01	.02	.02

Table 46. MBE Partial Eta Squared by Term Interaction (Part 4)

Term	walktrap_log_bic	louvain_log_bic	leiden_log_bic	walktrap_log_gic_3	louvain_log_gic_3	leiden_log_gic_3	walktrap_log_gic_4	louvain_log_gic_4	leiden_log_gic_4	walktrap_log_ebic	louvain_log_ebic	leiden_log_ebic
balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor	.02	.00	.00	.01	.00	.00	.00	.00	.00	.00	.00	.00
fct	.12	.22	.22	.09	.20	.21	.10	.19	.18	.10	.17	.18
items	.11	.19	.20	.12	.15	.15	.08	.09	.09	.07	.07	.07
linear	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
loading	.03	.03	.03	.01	.01	.01	.01	.04	.03	.24	.31	.31
responses	.02	.01	.00	.00	.01	.01	.03	.05	.06	.05	.07	.07
sample	.01	.04	.04	.01	.02	.02	.05	.06	.05	.15	.18	.19
balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:balance	.00	.01	.00	.00	.01	.00	.00	.01	.00	.00	.00	.00
fct:f_cor	.03	.04	.05	.01	.02	.03	.01	.02	.02	.00	.01	.01
fct:items	.01	.01	.02	.02	.01	.02	.02	.01	.01	.00	.00	.00
fct:linear	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:loading	.02	.06	.06	.02	.08	.08	.07	.14	.13	.11	.17	.17
fct:responses	.05	.06	.06	.02	.03	.03	.00	.00	.00	.00	.00	.00
fct:sample	.02	.05	.06	.02	.07	.07	.07	.11	.11	.07	.08	.09
items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
items:f_cor	.03	.03	.03	.03	.03	.03	.02	.02	.02	.02	.01	.01
linear:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
linear:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
linear:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
linear:loading	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
loading:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.01	.00	.00
loading:items	.11	.13	.13	.09	.08	.08	.04	.04	.04	.04	.04	.04
responses:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:items	.00	.01	.01	.01	.02	.02	.02	.02	.03	.01	.01	.01
responses:linear	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:loading	.02	.01	.01	.02	.02	.02	.06	.07	.07	.09	.10	.10
responses:sample	.01	.00	.00	.00	.01	.01	.05	.08	.08	.04	.05	.05
sample:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:f_cor	.00	.00	.00	.01	.00	.00	.00	.00	.00	.01	.01	.00
sample:items	.05	.10	.10	.04	.06	.06	.02	.02	.02	.01	.01	.01
sample:linear	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:loading	.09	.06	.06	.07	.02	.03	.13	.18	.17	.35	.39	.40
fct:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:items:f_cor	.01	.01	.01	.01	.01	.01	.01	.00	.00	.01	.00	.00

fct:linear:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:linear:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:linear:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:linear:loading	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.01	.00	.00	.00
fct:loading:f_cor	.01	.01	.01	.00	.00	.01	.00	.01	.01	.00	.00	.00
fct:loading:items	.02	.01	.01	.02	.01	.01	.01	.01	.00	.00	.00	.00
fct:responses:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:items	.01	.01	.01	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:linear	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:loading	.00	.00	.00	.01	.01	.01	.02	.01	.02	.02	.02	.02
fct:responses:sample	.03	.02	.03	.01	.01	.01	.01	.01	.01	.01	.01	.01
fct:sample:balance	.00	.01	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:sample:f_cor	.00	.00	.00	.01	.00	.01	.00	.00	.00	.00	.00	.00
fct:sample:items	.00	.00	.00	.01	.00	.00	.00	.00	.00	.00	.00	.00
fct:sample:linear	.00	.00	.00	.01	.00	.00	.00	.00	.00	.00	.00	.00
fct:sample:loading	.01	.02	.02	.01	.01	.01	.07	.08	.08	.09	.08	.08
items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
linear:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
linear:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
linear:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
linear:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
linear:loading:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
linear:loading:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
loading:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
loading:items:f_cor	.01	.01	.01	.01	.01	.01	.00	.00	.00	.00	.00	.00
responses:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:linear:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:linear:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:linear:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:linear:loading	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:loading:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:loading:items	.00	.00	.00	.00	.00	.00	.01	.01	.01	.01	.01	.01
responses:sample:balance	.00	.00	.00	.01	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:items	.00	.00	.00	.00	.01	.01	.01	.02	.02	.01	.01	.01
responses:sample:linear	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:loading	.02	.01	.01	.04	.01	.01	.08	.10	.09	.06	.06	.05
sample:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:linear:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:linear:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:linear:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:linear:loading	.00	.00	.01	.00	.00	.00	.01	.00	.00	.00	.00	.00
sample:loading:balance	.00	.00	.00	.00	.01	.00	.00	.00	.00	.00	.00	.00
sample:loading:f_cor	.01	.00	.00	.02	.01	.01	.01	.00	.00	.01	.00	.00
sample:loading:items	.05	.05	.05	.03	.01	.02	.02	.02	.02	.03	.03	.03
fct:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:linear:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:linear:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:linear:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:linear:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.01	.00	.00	.00

fct:linear:loading:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:linear:loading:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:loading:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:loading:items:f_cor	.00	.00	.00	.01	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.01	.00	.00
fct:responses:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:linear:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:linear:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:linear:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:linear:loading	.00	.00	.00	.00	.01	.01	.00	.01	.00	.00	.01	.01
fct:responses:loading:balance	.00	.00	.00	.00	.01	.00	.00	.00	.00	.00	.00	.00
fct:responses:loading:f_cor	.00	.01	.01	.00	.00	.00	.00	.01	.01	.00	.00	.00
fct:responses:loading:items	.00	.00	.00	.00	.00	.00	.01	.00	.00	.01	.01	.01
fct:responses:sample:balance	.00	.01	.00	.00	.00	.00	.00	.00	.00	.01	.01	.01
fct:responses:sample:f_cor	.00	.01	.01	.00	.01	.00	.02	.02	.01	.01	.01	.01
fct:responses:sample:items	.01	.01	.01	.00	.00	.00	.00	.01	.01	.01	.01	.01
fct:responses:sample:linear	.01	.01	.01	.01	.01	.01	.00	.00	.00	.00	.01	.01
fct:responses:sample:loading	.02	.02	.03	.03	.03	.03	.05	.06	.06	.03	.03	.03
fct:sample:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:sample:items:balance	.00	.00	.00	.00	.00	.00	.01	.00	.00	.01	.00	.00
fct:sample:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.01	.00	.00
fct:sample:linear:balance	.00	.00	.00	.00	.00	.00	.00	.01	.01	.00	.00	.00
fct:sample:linear:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:sample:linear:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:sample:linear:loading	.00	.01	.01	.01	.01	.01	.00	.00	.00	.00	.00	.00
fct:sample:loading:balance	.00	.00	.00	.00	.00	.00	.01	.01	.01	.00	.00	.00
fct:sample:loading:f_cor	.01	.01	.01	.02	.01	.02	.01	.02	.02	.01	.01	.01
fct:sample:loading:items	.00	.01	.01	.01	.00	.00	.01	.00	.00	.01	.01	.01
linear:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
linear:loading:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
linear:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
linear:loading:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
loading:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:linear:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:linear:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:linear:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:linear:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:linear:loading:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:linear:loading:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:loading:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:loading:items:balance	.00	.00	.00	.00	.01	.01	.00	.00	.00	.00	.00	.00
responses:loading:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.01	.00	.00
responses:sample:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.01
responses:sample:linear:balance	.00	.00	.00	.00	.00	.00	.00	.01	.01	.00	.00	.00
responses:sample:linear:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:linear:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:linear:loading	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:loading:balance	.00	.00	.00	.01	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:loading:f_cor	.00	.00	.00	.00	.00	.01	.01	.01	.01	.00	.00	.00
responses:sample:loading:items	.01	.03	.03	.00	.01	.01	.01	.01	.01	.01	.01	.01
sample:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:linear:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:linear:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00

sample:linear:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:linear:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:linear:loading:f_cor	.00	.00	.00	.00	.00	.00	.01	.00	.00	.01	.01	.01
sample:linear:loading:items	.00	.00	.00	.00	.00	.00	.00	.01	.01	.00	.00	.00
sample:loading:balance:f_cor	.00	.01	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:loading:items:f_cor	.00	.01	.01	.00	.00	.00	.01	.01	.01	.01	.01	.01
fct:linear:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:linear:loading:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:linear:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:linear:loading:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:loading:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:linear:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:linear:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:linear:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:linear:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:linear:loading:f_cor	.00	.00	.00	.00	.00	.00	.00	.01	.01	.00	.00	.00
fct:responses:linear:loading:items	.00	.00	.00	.00	.00	.01	.00	.00	.00	.00	.00	.00
fct:responses:loading:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:loading:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:sample:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:sample:items:balance	.00	.00	.00	.01	.01	.01	.00	.00	.00	.00	.00	.00
fct:responses:sample:items:f_cor	.01	.01	.01	.01	.01	.01	.00	.00	.00	.00	.00	.00
fct:responses:sample:linear:balance	.01	.00	.00	.01	.01	.01	.01	.01	.01	.00	.01	.00
fct:responses:sample:linear:f_cor	.01	.00	.01	.01	.01	.01	.01	.01	.01	.00	.00	.00
fct:responses:sample:linear:items	.01	.00	.00	.01	.00	.01	.01	.00	.01	.00	.00	.00
fct:responses:sample:linear:loading	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01
fct:responses:sample:loading:balance	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01
fct:responses:sample:loading:f_cor	.01	.01	.02	.01	.01	.01	.02	.02	.02	.02	.02	.02
fct:responses:sample:loading:items	.01	.01	.01	.01	.01	.01	.02	.02	.02	.01	.02	.01
fct:sample:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.01	.00	.00	.01	.00	.00
fct:sample:linear:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:sample:linear:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:sample:linear:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:sample:linear:loading:balance	.00	.01	.01	.01	.01	.01	.01	.00	.01	.00	.00	.00
fct:sample:linear:loading:f_cor	.00	.00	.00	.00	.00	.00	.01	.00	.00	.00	.00	.00
fct:sample:linear:loading:items	.01	.00	.00	.01	.01	.00	.01	.00	.00	.01	.01	.01
fct:sample:loading:balance:f_cor	.01	.01	.01	.01	.01	.01	.00	.00	.00	.00	.00	.01
fct:sample:loading:items:balance	.01	.00	.00	.00	.00	.00	.01	.01	.01	.01	.01	.01
fct:sample:loading:items:f_cor	.01	.01	.01	.00	.01	.01	.00	.01	.01	.01	.01	.01
linear:loading:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:linear:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:linear:loading:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:linear:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:linear:loading:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:loading:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:linear:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:linear:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:linear:items:f_cor	.00	.00	.00	.00	.00	.01	.00	.00	.00	.00	.00	.00
responses:sample:linear:loading:balance	.00	.00	.00	.00	.00	.00	.01	.01	.01	.00	.00	.00
responses:sample:linear:loading:f_cor	.00	.00	.01	.01	.01	.00	.00	.01	.00	.00	.00	.00
responses:sample:linear:loading:items	.00	.00	.00	.00	.00	.00	.00	.01	.00	.00	.00	.00
responses:sample:loading:balance:f_cor	.00	.01	.00	.00	.01	.01	.00	.00	.00	.01	.01	.01
responses:sample:loading:items:balance	.01	.00	.01	.01	.01	.01	.00	.00	.00	.00	.01	.01
responses:sample:loading:items:f_cor	.01	.01	.01	.01	.00	.00	.00	.00	.00	.01	.01	.01

sample:linear:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:linear:loading:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:linear:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:linear:loading:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:loading:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:linear:loading:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:linear:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.01	.00	.00	.00	.00	.00
fct:responses:linear:loading:balance:f_cor	.00	.00	.00	.00	.00	.00	.01	.00	.00	.00	.01	.01
fct:responses:linear:loading:items:balance	.00	.00	.00	.00	.01	.01	.01	.00	.00	.00	.00	.00
fct:responses:linear:loading:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:loading:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:sample:items:balance:f_cor	.00	.00	.00	.00	.01	.00	.01	.01	.01	.01	.01	.01
fct:responses:sample:linear:balance:f_cor	.01	.00	.01	.01	.01	.01	.00	.01	.01	.00	.00	.00
fct:responses:sample:linear:items:balance	.01	.00	.00	.01	.01	.01	.01	.01	.00	.01	.00	.00
fct:responses:sample:linear:items:f_cor	.01	.00	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01
fct:responses:sample:linear:loading:balance	.01	.01	.01	.01	.01	.01	.02	.02	.02	.01	.01	.01
fct:responses:sample:linear:loading:f_cor	.01	.01	.01	.01	.01	.01	.02	.02	.02	.01	.01	.01
fct:responses:sample:linear:loading:items	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01
fct:responses:sample:loading:balance:f_cor	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01
fct:responses:sample:loading:items:balance	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01
fct:responses:sample:loading:items:f_cor	.02	.02	.02	.01	.01	.01	.01	.01	.01	.01	.01	.01
fct:sample:linear:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:sample:linear:loading:balance:f_cor	.01	.00	.00	.01	.01	.00	.00	.00	.00	.00	.00	.00
fct:sample:linear:loading:items:balance	.01	.00	.00	.00	.00	.00	.01	.00	.00	.00	.01	.00
fct:sample:linear:loading:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:sample:loading:items:balance:f_cor	.00	.01	.01	.01	.00	.01	.01	.01	.01	.01	.01	.01
responses:linear:loading:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:linear:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:linear:loading:balance:f_cor	.00	.00	.00	.00	.01	.01	.00	.00	.00	.00	.00	.00
responses:sample:linear:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:linear:loading:items:f_cor	.00	.00	.00	.00	.01	.01	.00	.00	.00	.00	.00	.01
responses:sample:loading:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:linear:loading:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:linear:loading:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.01	.00	.00	.00	.00	.00
fct:responses:sample:linear:items:balance:f_cor	.01	.00	.00	.01	.00	.00	.01	.01	.01	.01	.01	.01
fct:responses:sample:linear:loading:balance:f_cor	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01
fct:responses:sample:linear:loading:items:balance	.01	.01	.02	.01	.02	.02	.01	.01	.01	.01	.01	.01
fct:responses:sample:linear:loading:items:f_cor	.01	.01	.01	.01	.01	.01	.01	.02	.02	.01	.01	.01
fct:responses:sample:loading:items:balance:f_cor	.01	.01	.01	.01	.01	.01	.01	.01	.02	.01	.01	.01
fct:sample:linear:loading:items:balance:f_cor	.01	.01	.01	.00	.00	.00	.00	.01	.01	.00	.00	.00
responses:sample:linear:loading:items:balance:f_cor	.00	.00	.00	.00	.01	.01	.00	.01	.01	.00	.00	.00
fct:responses:sample:linear:loading:items:balance:f_cor	.01	.01	.01	.00	.01	.01	.01	.02	.01	.01	.02	.02

Table 47. MBE Partial Eta Squared by Term Interaction (Part 5)

Term	R2Z_walktrap	R2Z_louvain	R2Z_leiden	fspe	fspe_none	fspe_geominQ	fspe_varimax	fspe_oblimin	EGAnet	PA_FA	PA_FA_none	PA_FA_geominQ	PA_FA_varimax	PA_FA_oblimin	PA_PC	PA_PC_none	PA_PC_geominQ	PA_PC_varimax	PA_PC_oblimin
balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.03	.00	.00	.00	.00	.00	.00	.00	.00	.00
f_cor	.22	.03	.03	.30	.00	.00	.00	.00	.07	.04	.00	.00	.00	.00	.52	.00	.00	.00	.00
fct	.58	.50	.50	.30	1.0	1.0	1.0	1.0	.11	.12	1.0	1.0	1.0	1.0	.10	1.0	1.0	1.0	1.0
items	.02	.19	.18	.09	.00	.00	.00	.00	.09	.44	.00	.00	.00	.00	.29	.00	.00	.00	.00
linear	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00

loading	.49	.07	.09	.50	.00	.00	.00	.00	.10	.19	.00	.00	.00	.00	.03	.00	.00	.00	.00
responses	.08	.01	.00	.10	.00	.00	.00	.00	.04	.67	.00	.00	.00	.00	.29	.00	.00	.00	.00
sample	.35	.02	.03	.19	.00	.00	.00	.00	.06	.02	.00	.00	.00	.00	.00	.00	.00	.00	.00
balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.01	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:f_cor	.10	.06	.06	.14	.00	.00	.00	.00	.03	.00	.00	.00	.00	.00	.23	.00	.00	.00	.00
fct:items	.01	.01	.01	.02	.00	.00	.00	.00	.01	.03	.00	.00	.00	.00	.10	.00	.00	.00	.00
fct:linear	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:loading	.26	.23	.25	.25	.00	.00	.00	.00	.09	.11	.00	.00	.00	.00	.01	.00	.00	.00	.00
fct:responses	.03	.03	.03	.04	.00	.00	.00	.00	.00	.26	.00	.00	.00	.00	.12	.00	.00	.00	.00
fct:sample	.17	.19	.20	.07	.00	.00	.00	.00	.03	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.01	.00	.00	.00	.00	.00	.00	.00	.00	.00
items:f_cor	.01	.02	.03	.01	.00	.00	.00	.00	.04	.00	.00	.00	.00	.00	.11	.00	.00	.00	.00
linear:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
linear:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
linear:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
linear:loading	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.02	.00	.00	.00	.00	.00	.00	.00	.00	.00
loading:f_cor	.03	.00	.00	.22	.00	.00	.00	.00	.01	.01	.00	.00	.00	.00	.05	.00	.00	.00	.00
loading:items	.02	.10	.10	.05	.00	.00	.00	.00	.02	.41	.00	.00	.00	.00	.05	.00	.00	.00	.00
responses:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:f_cor	.00	.00	.00	.03	.00	.00	.00	.00	.00	.15	.00	.00	.00	.00	.02	.00	.00	.00	.00
responses:items	.00	.01	.01	.00	.00	.00	.00	.00	.01	.27	.00	.00	.00	.00	.05	.00	.00	.00	.00
responses:linear	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:loading	.01	.00	.00	.04	.00	.00	.00	.00	.09	.54	.00	.00	.00	.00	.32	.00	.00	.00	.00
responses:sample	.00	.00	.00	.01	.00	.00	.00	.00	.07	.12	.00	.00	.00	.00	.10	.00	.00	.00	.00
sample:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:f_cor	.00	.00	.00	.03	.00	.00	.00	.00	.00	.04	.00	.00	.00	.00	.03	.00	.00	.00	.00
sample:items	.01	.04	.04	.01	.00	.00	.00	.00	.00	.02	.00	.00	.00	.00	.01	.00	.00	.00	.00
sample:linear	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:loading	.05	.01	.01	.13	.00	.00	.00	.00	.09	.01	.00	.00	.00	.00	.03	.00	.00	.00	.00
fct:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.01	.00	.00	.00	.00	.02	.00	.00	.00	.00
fct:linear:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:linear:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:linear:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:linear:loading	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:loading:f_cor	.01	.00	.01	.07	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01
fct:loading:items	.01	.00	.00	.01	.00	.00	.00	.00	.00	.01	.00	.00	.00	.00	.01	.00	.00	.00	.00
fct:responses:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:f_cor	.00	.00	.00	.01	.01	.01	.01	.01	.00	.07	.01	.01	.01	.01	.00	.01	.01	.01	.01
fct:responses:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.05	.00	.00	.00	.00	.02	.00	.00	.00	.00
fct:responses:linear	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:loading	.00	.01	.00	.01	.01	.01	.01	.01	.01	.19	.01	.01	.01	.01	.12	.01	.01	.01	.01
fct:responses:sample	.01	.01	.01	.01	.01	.01	.01	.01	.01	.02	.01	.01	.01	.01	.03	.01	.01	.01	.01
fct:sample:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:sample:f_cor	.00	.01	.00	.01	.01	.01	.01	.01	.00	.02	.01	.01	.01	.01	.01	.01	.01	.01	.01
fct:sample:items	.01	.02	.01	.00	.00	.00	.00	.00	.00	.01	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:sample:linear	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:sample:loading	.06	.03	.03	.04	.01	.01	.01	.01	.02	.00	.01	.01	.01	.01	.01	.01	.01	.01	.01
items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
linear:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
linear:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
linear:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
linear:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
linear:loading:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00

linear:loading:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
loading:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.01	.00	.00	.00	.00	.00	.00	.00	.00	.00
loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.01	.00	.00	.00	.00	.00	.00	.00	.00	.00
loading:items:f_cor	.01	.00	.00	.01	.00	.00	.00	.00	.00	.01	.00	.00	.00	.00	.02	.00	.00	.00	.00
responses:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.02	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:linear:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:linear:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:linear:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:linear:loading	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:loading:f_cor	.01	.00	.00	.01	.00	.00	.00	.00	.00	.04	.00	.00	.00	.00	.01	.00	.00	.00	.00
responses:loading:items	.00	.00	.00	.00	.00	.00	.00	.00	.01	.19	.00	.00	.00	.00	.08	.00	.00	.00	.00
responses:sample:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.01	.00	.00	.00	.00
responses:sample:items	.00	.00	.00	.00	.00	.00	.00	.00	.01	.01	.00	.00	.00	.00	.01	.00	.00	.00	.00
responses:sample:linear	.00	.01	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:loading	.02	.01	.01	.01	.00	.00	.00	.00	.12	.03	.00	.00	.00	.00	.08	.00	.00	.00	.00
sample:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:items:balance	.00	.00	.00	.00	.01	.01	.01	.01	.00	.00	.01	.01	.01	.01	.00	.01	.01	.01	.01
sample:items:f_cor	.00	.00	.00	.01	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.01	.00	.00	.00	.00
sample:linear:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:linear:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:linear:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:linear:loading	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:loading:f_cor	.06	.01	.02	.03	.00	.00	.00	.00	.01	.04	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:loading:items	.01	.01	.01	.00	.00	.00	.00	.00	.01	.00	.00	.00	.00	.00	.01	.00	.00	.00	.00
fct:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:linear:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:linear:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:linear:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:linear:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:linear:loading:f_cor	.00	.00	.00	.00	.01	.01	.01	.01	.00	.00	.01	.01	.01	.01	.00	.01	.01	.01	.01
fct:linear:loading:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:loading:balance:f_cor	.00	.00	.00	.00	.01	.01	.01	.01	.00	.01	.01	.01	.01	.01	.00	.01	.01	.01	.01
fct:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.01	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:loading:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.01	.00	.00	.00	.00	.01	.00	.00	.00	.00
fct:responses:balance:f_cor	.00	.00	.00	.00	.01	.01	.01	.01	.00	.00	.01	.01	.01	.01	.00	.01	.01	.01	.01
fct:responses:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:linear:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:linear:f_cor	.00	.00	.00	.00	.01	.01	.01	.01	.00	.00	.01	.01	.01	.01	.00	.01	.01	.01	.01
fct:responses:linear:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:linear:loading	.00	.00	.00	.00	.01	.01	.01	.01	.00	.00	.01	.01	.01	.01	.00	.01	.01	.01	.01
fct:responses:loading:balance	.00	.01	.01	.00	.01	.01	.01	.01	.00	.00	.01	.01	.01	.01	.00	.01	.01	.01	.01
fct:responses:loading:f_cor	.01	.01	.01	.01	.01	.01	.01	.01	.01	.02	.01	.01	.01	.01	.00	.01	.01	.01	.01
fct:responses:loading:items	.00	.00	.00	.00	.00	.00	.00	.00	.01	.03	.00	.00	.00	.00	.03	.00	.00	.00	.00
fct:responses:sample:balance	.01	.00	.00	.01	.01	.01	.01	.01	.00	.00	.01	.01	.01	.01	.00	.01	.01	.01	.01
fct:responses:sample:f_cor	.00	.00	.00	.00	.02	.02	.02	.02	.01	.01	.02	.02	.02	.02	.00	.02	.02	.02	.02
fct:responses:sample:items	.00	.01	.01	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:sample:linear	.00	.01	.00	.01	.01	.01	.01	.01	.01	.00	.01	.01	.01	.01	.00	.01	.01	.01	.01
fct:responses:sample:loading	.02	.01	.01	.01	.02	.02	.02	.02	.02	.01	.02	.02	.02	.02	.02	.02	.02	.02	.02
fct:sample:balance:f_cor	.00	.00	.00	.00	.01	.01	.01	.01	.00	.00	.01	.01	.01	.01	.00	.01	.01	.01	.01
fct:sample:items:balance	.01	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:sample:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:sample:linear:balance	.00	.01	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00

fct:sample:linear:f_cor	.00	.00	.00	.00	.01	.01	.01	.01	.00	.00	.01	.01	.01	.01	.00	.01	.01	.01	.01
fct:sample:linear:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:sample:linear:loading	.00	.00	.00	.01	.01	.01	.01	.01	.00	.01	.01	.01	.01	.01	.00	.01	.01	.01	.01
fct:sample:loading:balance	.00	.01	.01	.00	.01	.01	.01	.01	.00	.01	.01	.01	.01	.01	.00	.01	.01	.01	.01
fct:sample:loading:f_cor	.04	.04	.03	.01	.02	.02	.02	.02	.01	.01	.02	.02	.02	.02	.00	.02	.02	.02	.02
fct:sample:loading:items	.01	.01	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
linear:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
linear:loading:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
linear:loading:items:balance	.00	.00	.00	.00	.01	.01	.01	.01	.00	.00	.01	.01	.01	.01	.00	.01	.01	.01	.01
linear:loading:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
loading:items:balance:f_cor	.00	.00	.00	.00	.01	.01	.01	.01	.00	.00	.01	.01	.01	.01	.00	.01	.01	.01	.01
responses:items:balance:f_cor	.00	.00	.00	.00	.01	.01	.01	.01	.00	.00	.01	.01	.01	.01	.00	.01	.01	.01	.01
responses:linear:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:linear:items:balance	.00	.00	.00	.00	.01	.01	.01	.01	.00	.00	.01	.01	.01	.01	.00	.01	.01	.01	.01
responses:linear:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:linear:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:linear:loading:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:linear:loading:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:loading:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:loading:items:balance	.00	.00	.00	.00	.01	.01	.01	.01	.00	.00	.01	.01	.01	.01	.00	.01	.01	.01	.01
responses:loading:items:f_cor	.00	.00	.00	.01	.00	.00	.00	.00	.00	.01	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:items:balance	.00	.00	.00	.00	.01	.01	.01	.01	.00	.00	.01	.01	.01	.01	.00	.01	.01	.01	.01
responses:sample:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:linear:balance	.00	.00	.00	.00	.00	.00	.00	.00	.01	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:linear:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:linear:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:linear:loading	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:loading:balance	.01	.00	.00	.01	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:loading:f_cor	.01	.01	.00	.03	.00	.00	.00	.00	.01	.01	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:loading:items	.00	.01	.01	.00	.00	.00	.00	.00	.01	.00	.00	.00	.00	.00	.01	.00	.00	.00	.00
sample:items:balance:f_cor	.00	.00	.00	.00	.01	.01	.01	.01	.00	.00	.01	.01	.01	.01	.00	.01	.01	.01	.01
sample:linear:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:linear:items:balance	.00	.00	.00	.00	.01	.01	.01	.01	.00	.00	.01	.01	.01	.01	.00	.01	.01	.01	.01
sample:linear:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:linear:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:linear:loading:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:linear:loading:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:loading:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:loading:items:balance	.00	.00	.00	.00	.01	.01	.01	.01	.00	.00	.01	.01	.01	.01	.00	.01	.01	.01	.01
sample:loading:items:f_cor	.00	.01	.00	.03	.00	.00	.00	.00	.01	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:linear:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:linear:loading:balance:f_cor	.00	.00	.00	.00	.01	.01	.01	.01	.00	.00	.01	.01	.01	.01	.00	.01	.01	.01	.01
fct:linear:loading:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:linear:loading:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:loading:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:linear:balance:f_cor	.00	.00	.00	.00	.01	.01	.01	.01	.00	.00	.01	.01	.01	.01	.00	.01	.01	.01	.01
fct:responses:linear:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:linear:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:linear:loading:balance	.01	.00	.00	.00	.01	.01	.01	.01	.00	.00	.01	.01	.01	.01	.00	.01	.01	.01	.01
fct:responses:linear:loading:f_cor	.00	.00	.00	.00	.02	.02	.02	.02	.00	.00	.02	.02	.02	.02	.00	.02	.02	.02	.02
fct:responses:linear:loading:items	.00	.01	.00	.00	.00	.00	.00	.00	.01	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:loading:balance:f_cor	.00	.00	.00	.00	.02	.02	.02	.02	.00	.00	.02	.02	.02	.02	.00	.02	.02	.02	.02
fct:responses:loading:items:balance	.01	.00	.00	.00	.00	.00	.00	.00	.00	.01	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:loading:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:sample:balance:f_cor	.01	.01	.00	.01	.02	.02	.02	.02	.01	.01	.02	.02	.02	.02	.00	.02	.02	.02	.02
fct:responses:sample:items:balance	.00	.00	.00	.01	.00	.00	.00	.00	.01	.01	.00	.00	.00	.00	.00	.00	.00	.00	.00

fct:responses:sample:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.01	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:sample:linear:balance	.00	.00	.00	.00	.01	.01	.01	.01	.01	.00	.01	.01	.01	.01	.00	.01	.01	.01	.01
fct:responses:sample:linear:f_cor	.00	.00	.00	.00	.02	.02	.02	.02	.01	.01	.02	.02	.02	.02	.00	.02	.02	.02	.02
fct:responses:sample:linear:items	.00	.00	.01	.00	.00	.00	.00	.00	.01	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:sample:linear:loading	.01	.01	.01	.01	.02	.02	.02	.02	.01	.01	.02	.02	.02	.02	.00	.02	.02	.02	.02
fct:responses:sample:loading:balance	.01	.01	.01	.01	.02	.02	.02	.02	.01	.01	.02	.02	.02	.02	.00	.02	.02	.02	.02
fct:responses:sample:loading:f_cor	.01	.01	.01	.02	.03	.03	.03	.03	.02	.01	.03	.03	.03	.03	.00	.03	.03	.03	.03
fct:responses:sample:loading:items	.01	.01	.01	.01	.00	.00	.00	.00	.01	.01	.00	.00	.00	.00	.01	.00	.00	.00	.00
fct:sample:items:balance:f_cor	.01	.00	.00	.00	.01	.01	.01	.01	.00	.00	.01	.01	.01	.01	.00	.01	.01	.01	.01
fct:sample:linear:balance:f_cor	.00	.01	.01	.00	.01	.01	.01	.01	.00	.00	.01	.01	.01	.01	.00	.01	.01	.01	.01
fct:sample:linear:items:balance	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:sample:linear:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:sample:linear:loading:balance	.01	.00	.00	.00	.01	.01	.01	.01	.00	.00	.01	.01	.01	.01	.00	.01	.01	.01	.01
fct:sample:linear:loading:f_cor	.01	.01	.01	.01	.02	.02	.02	.02	.01	.00	.02	.02	.02	.02	.00	.02	.02	.02	.02
fct:sample:linear:loading:items	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:sample:loading:balance:f_cor	.00	.00	.01	.00	.02	.02	.02	.02	.00	.00	.02	.02	.02	.02	.00	.02	.02	.02	.02
fct:sample:loading:items:balance	.00	.01	.00	.00	.00	.00	.00	.00	.01	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:sample:loading:items:f_cor	.01	.01	.00	.01	.00	.00	.00	.00	.01	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
linear:loading:items:balance:f_cor	.00	.00	.00	.00	.01	.01	.01	.01	.00	.00	.01	.01	.01	.01	.00	.01	.01	.01	.01
responses:linear:items:balance:f_cor	.00	.00	.00	.00	.01	.01	.01	.01	.00	.00	.01	.01	.01	.01	.00	.01	.01	.01	.01
responses:linear:loading:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:linear:loading:items:balance	.00	.00	.00	.00	.01	.01	.01	.01	.00	.00	.01	.01	.01	.01	.00	.01	.01	.01	.01
responses:linear:loading:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:loading:items:balance:f_cor	.00	.00	.00	.00	.01	.01	.01	.01	.00	.00	.01	.01	.01	.01	.00	.01	.01	.01	.01
responses:sample:items:balance:f_cor	.00	.00	.00	.00	.02	.02	.02	.02	.00	.00	.02	.02	.02	.02	.00	.02	.02	.02	.02
responses:sample:linear:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:linear:items:balance	.00	.00	.00	.00	.01	.01	.01	.01	.00	.00	.01	.01	.01	.01	.00	.01	.01	.01	.01
responses:sample:linear:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:linear:loading:balance	.00	.00	.00	.00	.00	.00	.00	.00	.01	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:linear:loading:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.01	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:linear:loading:items	.00	.01	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:loading:balance:f_cor	.00	.00	.00	.01	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:loading:items:balance	.00	.00	.00	.00	.02	.02	.02	.02	.00	.00	.02	.02	.02	.02	.00	.02	.02	.02	.02
responses:sample:loading:items:f_cor	.01	.00	.00	.01	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:linear:items:balance:f_cor	.00	.00	.00	.00	.01	.01	.01	.01	.00	.00	.01	.01	.01	.01	.00	.01	.01	.01	.01
sample:linear:loading:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:linear:loading:items:balance	.00	.00	.00	.00	.02	.02	.02	.02	.00	.00	.02	.02	.02	.02	.00	.02	.02	.02	.02
sample:linear:loading:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:loading:items:balance:f_cor	.00	.00	.00	.00	.02	.02	.02	.02	.00	.00	.02	.02	.02	.02	.00	.02	.02	.02	.02
fct:linear:loading:items:balance:f_cor	.00	.00	.00	.00	.01	.01	.01	.01	.00	.00	.01	.01	.01	.01	.00	.01	.01	.01	.01
fct:responses:linear:items:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:linear:loading:balance:f_cor	.00	.00	.01	.00	.02	.02	.02	.02	.01	.00	.02	.02	.02	.02	.00	.02	.02	.02	.02
fct:responses:linear:loading:items:balance	.00	.00	.00	.00	.01	.01	.01	.01	.00	.00	.01	.01	.01	.01	.00	.01	.01	.01	.01
fct:responses:linear:loading:items:f_cor	.00	.01	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:loading:items:balance:f_cor	.00	.00	.01	.00	.01	.01	.01	.01	.00	.00	.01	.01	.01	.01	.00	.01	.01	.01	.01
fct:responses:sample:items:balance:f_cor	.01	.00	.00	.00	.02	.02	.02	.02	.01	.01	.02	.02	.02	.02	.00	.02	.02	.02	.02
fct:responses:sample:linear:balance:f_cor	.01	.01	.01	.00	.03	.03	.03	.03	.01	.00	.03	.03	.03	.03	.00	.03	.03	.03	.03
fct:responses:sample:linear:items:balance	.01	.00	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01
fct:responses:sample:linear:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.01	.01	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:responses:sample:linear:loading:balance	.01	.01	.01	.01	.03	.03	.03	.03	.01	.01	.03	.03	.03	.03	.01	.03	.03	.03	.03
fct:responses:sample:linear:loading:f_cor	.01	.01	.01	.01	.05	.05	.05	.05	.01	.01	.05	.05	.05	.05	.00	.05	.05	.05	.05
fct:responses:sample:linear:loading:items	.01	.01	.02	.01	.00	.00	.00	.00	.01	.01	.00	.00	.00	.00	.01	.00	.00	.00	.00
fct:responses:sample:loading:balance:f_cor	.01	.01	.01	.01	.05	.05	.05	.05	.02	.01	.05	.05	.05	.05	.00	.05	.05	.05	.05
fct:responses:sample:loading:items:balance	.01	.01	.01	.01	.01	.01	.01	.01	.00	.01	.01	.01	.01	.01	.01	.01	.01	.01	.01
fct:responses:sample:loading:items:f_cor	.01	.01	.01	.01	.00	.00	.00	.00	.01	.01	.00	.00	.00	.00	.01	.00	.00	.00	.00
fct:sample:linear:items:balance:f_cor	.00	.00	.00	.00	.01	.01	.01	.01	.00	.00	.01	.01	.01	.01	.00	.01	.01	.01	.01
fct:sample:linear:loading:balance:f_cor	.00	.01	.01	.00	.04	.04	.04	.04	.00	.00	.04	.04	.04	.04	.00	.04	.04	.04	.04
fct:sample:linear:loading:items:balance	.00	.01	.01	.01	.01	.01	.01	.01	.00	.00	.01	.01	.01	.01	.01	.01	.01	.01	.01

fct:sample:linear:loading:items:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.01	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
fct:sample:loading:items:balance:f_cor	.01	.01	.00	.00	.02	.02	.02	.02	.01	.01	.02	.02	.02	.02	.00	.02	.02	.02	.02
responses:linear:loading:items:balance:f_cor	.00	.00	.00	.00	.02	.02	.02	.02	.00	.00	.02	.02	.02	.02	.00	.02	.02	.02	.02
responses:sample:linear:items:balance:f_cor	.00	.00	.00	.00	.02	.02	.02	.02	.00	.00	.02	.02	.02	.02	.00	.02	.02	.02	.02
responses:sample:linear:loading:balance:f_cor	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00
responses:sample:linear:loading:items:balance	.01	.00	.00	.01	.03	.03	.03	.03	.00	.00	.03	.03	.03	.03	.00	.03	.03	.03	.03
responses:sample:linear:loading:items:f_cor	.01	.00	.00	.01	.01	.01	.01	.01	.00	.00	.01	.01	.01	.01	.00	.01	.01	.01	.01
responses:sample:loading:items:balance:f_cor	.00	.00	.00	.00	.04	.04	.04	.04	.00	.00	.04	.04	.04	.04	.00	.04	.04	.04	.04
sample:linear:loading:items:balance:f_cor	.00	.00	.00	.00	.03	.03	.03	.03	.00	.00	.03	.03	.03	.03	.00	.03	.03	.03	.03
fct:responses:linear:loading:items:balance:f_cor	.00	.00	.00	.00	.01	.01	.01	.01	.00	.00	.01	.01	.01	.01	.00	.01	.01	.01	.01
fct:responses:sample:linear:items:balance:f_cor	.00	.00	.00	.00	.02	.02	.02	.02	.01	.00	.02	.02	.02	.02	.00	.02	.02	.02	.02
fct:responses:sample:linear:loading:balance:f_cor	.01	.01	.01	.01	.07	.07	.07	.07	.02	.01	.07	.07	.07	.07	.01	.07	.07	.07	.07
fct:responses:sample:linear:loading:items:balance	.02	.01	.01	.01	.02	.02	.02	.02	.01	.01	.02	.02	.02	.02	.00	.02	.02	.02	.02
fct:responses:sample:linear:loading:items:f_cor	.01	.01	.01	.01	.00	.00	.00	.00	.01	.01	.00	.00	.00	.00	.01	.00	.00	.00	.00
fct:responses:sample:loading:items:balance:f_cor	.01	.01	.01	.01	.03	.03	.03	.03	.02	.01	.03	.03	.03	.03	.01	.03	.03	.03	.03
fct:sample:linear:loading:items:balance:f_cor	.00	.01	.00	.01	.02	.02	.02	.02	.01	.00	.02	.02	.02	.02	.01	.02	.02	.02	.02
responses:sample:linear:loading:items:balance:f_cor	.00	.00	.00	.00	.04	.04	.04	.04	.00	.00	.04	.04	.04	.04	.00	.04	.04	.04	.04
fct:responses:sample:linear:loading:items:balance:f_cor	.01	.01	.01	.01	.04	.04	.04	.04	.01	.01	.04	.04	.04	.04	.01	.04	.04	.04	.04

Appendix C: Study 2 Clusterings

Table 48. Clusterings of 435 Terms by Algorithm

	Spectral (1)	Spectral (2)	Ward’ s (D-B)	Ward’ s (K-L)	Average (K-L)	Mclust
Abrupt	2	2	1	1	1	1
Absent.Minded	2	2	1	1	1	2
Abusive	2	2	1	1	1	3
Accommodating	1	1	2	2	2	4
Active	1	1	2	2	2	4
Adaptable	1	1	2	2	2	4
Adventurous	1	1	2	2	2	4
Affectionate	1	1	2	2	2	4
Aggressive	1	1	2	2	1	5
Agreeable	1	1	2	2	2	4
Aimless	2	2	1	1	1	3
Alert	1	1	2	2	2	4
Aloof	2	2	1	1	1	6
Altruistic	1	1	2	2	2	5
Ambitious	1	1	2	2	2	4
Amiable	1	1	2	2	2	4

Analytical	1	1	2	2	2	7
Animated	1	1	2	2	1	5
Antagonistic	2	2	1	1	1	2
Anxious	1	1	1	1	2	5
Apathetic	2	2	1	1	1	2
Argumentative	1	1	1	1	1	1
Articulate	1	1	2	2	2	7
Artistic	1	1	2	2	2	5
Assertive	1	1	2	2	2	5
Assured	1	1	2	2	2	7
Autonomous	1	1	2	2	2	5
Bashful	2	2	1	1	1	6
Belligerent	2	2	1	1	1	2
Benevolent	1	1	2	2	2	5
Bigoted	2	2	1	1	1	3
Bitter	2	2	1	1	1	3
Bland	2	2	1	1	1	3
Boastful	2	2	1	1	1	1
Boisterous	2	2	1	1	1	1
Bold	1	1	2	2	2	5
Bossy	1	1	1	1	1	1
Brave	1	1	2	2	2	5
Bright	1	1	2	2	2	4
Bullheaded	1	1	1	1	1	1
Callous	2	2	1	1	1	2
Candid	1	1	2	2	2	5
Carefree	1	1	2	2	2	5
Careful	1	1	2	2	2	7
Careless	2	2	1	1	1	2
Casual	1	1	2	2	2	4
Cautious	1	1	2	2	2	7
Charitable	1	1	2	2	2	4
Cheerful	1	1	2	2	2	4
Clever	1	1	2	2	2	4
Coarse	2	2	1	1	1	3
Cold	2	2	1	1	1	3
Combative	2	2	1	1	1	1
Communicative	1	1	2	2	2	4
Compassionate	1	1	2	2	2	4
Competitive	1	1	2	2	2	5
Complex	1	1	2	2	2	5
Compliant	1	1	2	2	2	5
Compulsive	1	1	2	2	2	5
Conceited	2	2	1	1	1	2
Concise	1	1	2	2	2	7

Condescending	2	2	1	1	1	1
Confident	1	1	2	2	2	4
Conscientious	1	1	2	2	2	4
Conservative	1	1	2	2	2	6
Considerate	1	1	2	2	2	4
Consistent	1	1	2	2	2	7
Contemplative	1	1	2	2	2	7
Controlled	1	1	2	2	2	7
Conventional	1	1	2	2	2	7
Cooperative	1	1	2	2	2	4
Cordial	1	1	2	2	2	4
Courageous	1	1	2	2	2	5
Courteous	1	1	2	2	2	4
Cowardly	2	2	1	1	1	2
Crabby	2	2	1	1	1	2
Crafty	1	1	1	1	1	1
Cranky	2	2	1	1	1	2
Creative	1	1	2	2	2	4
Critical	1	1	1	1	1	5
Cruel	2	2	1	1	1	3
Cultured	1	1	2	2	2	7
Cunning	1	1	1	1	1	1
Curious	1	1	2	2	2	4
Cynical	2	2	1	1	1	2
Daring	1	1	2	2	2	5
Deceitful	2	2	1	1	1	3
Decisive	1	1	2	2	2	7
Deep	1	1	2	2	2	4
Defensive	1	1	1	1	2	1
Deliberate	1	1	2	2	2	7
Demanding	1	1	1	1	1	1
Demonstrative	1	1	2	2	2	5
Dependable	1	1	2	2	2	4
Dependent	1	1	1	1	1	6
Detached	2	2	1	1	1	6
Devious	2	2	1	1	1	1
Dignified	1	1	2	2	2	7
Diplomatic	1	1	2	2	2	7
Direct	1	1	2	2	2	4
Discreet	1	1	2	2	2	7
Dishonest	2	2	1	1	1	3
Disorderly	2	2	1	1	1	2
Disorganized	2	2	1	1	1	2
Disrespectful	2	2	1	1	1	3
Distrustful	2	2	1	1	1	2

Docile	2	2	1	1	1	6
Dogmatic	2	2	1	1	1	1
Dominant	1	1	2	2	1	1
Domineering	1	1	2	2	1	1
Down.To.Earth	1	1	2	2	2	7
Dull	2	2	1	1	1	3
Earnest	1	1	2	2	2	4
Earthy	1	1	2	2	2	5
Easygoing	1	1	2	2	2	4
Economical	1	1	2	2	2	7
Efficient	1	1	2	2	2	7
Egocentric	2	2	1	1	1	1
Egotistical	2	2	1	1	1	1
Eloquent	1	1	2	2	2	5
Emotional	1	1	2	2	2	4
Empathic	1	1	2	2	2	5
Energetic	1	1	2	2	2	4
Enterprising	1	1	2	2	2	5
Enthusiastic	1	1	2	2	2	4
Envious	1	1	1	1	1	1
Erratic	2	2	1	1	1	2
Ethical	1	1	2	2	2	7
Exacting	1	1	2	2	2	7
Excitable	1	1	2	2	2	4
Exhibitionistic	2	2	1	1	1	2
Explosive	2	2	1	1	1	1
Expressive	1	1	2	2	2	4
Extravagant	1	1	1	1	1	1
Extroverted	1	1	2	2	1	5
Faultfinding	1	1	1	1	1	1
Fearful	2	2	1	1	1	6
Feminine	1	1	1	1	3	6
Finicky	2	2	1	1	1	1
Firm	1	1	2	2	2	7
Flamboyant	1	1	1	1	1	1
Flexible	1	1	2	2	2	4
Flirtatious	1	1	2	2	1	5
Foolhardy	2	2	1	1	1	2
Forceful	1	1	2	2	1	1
Foresighted	1	1	2	2	2	7
Forgetful	2	2	1	1	1	1
Formal	1	1	1	1	1	6
Frank	1	1	2	2	2	4
Fretful	2	2	1	1	1	6
Friendly	1	1	2	2	2	4

Frivolous	2	2	1	1	1	2
Generous	1	1	2	2	2	4
Genial	1	1	2	2	2	4
Gossipy	2	2	1	1	1	1
Greedy	2	2	1	1	1	2
Gregarious	1	1	2	2	2	5
Grumpy	2	2	1	1	1	2
Gullible	1	1	1	1	1	6
Haphazard	2	2	1	1	1	2
Happy.Go.Lucky	1	1	2	2	2	5
Harsh	2	2	1	1	1	3
Hearty	1	1	2	2	2	5
Helpful	1	1	2	2	2	4
High.Strung	1	1	1	1	1	1
Honest	1	1	2	2	2	4
Humble	1	1	2	2	2	7
Humorless	2	2	1	1	1	3
Humorous	1	1	2	2	2	4
Hypocritical	2	2	1	1	1	2
Idealistic	1	1	2	2	2	5
Ignorant	2	2	1	1	1	3
Illogical	2	2	1	1	1	2
Imaginative	1	1	2	2	2	4
Immature	2	2	1	1	1	2
Impartial	1	1	2	2	1	6
Impatient	1	1	1	1	1	1
Impersonal	2	2	1	1	1	3
Impetuous	1	1	2	2	2	1
Impolite	2	2	1	1	1	3
Impractical	2	2	1	1	1	2
Impulsive	1	1	2	2	2	5
Inarticulate	2	2	1	1	1	2
Inconsiderate	2	2	1	1	1	3
Inconsistent	2	2	1	1	1	2
Indecisive	2	2	1	1	1	6
Independent	1	1	2	2	2	4
Indirect	2	2	1	1	1	6
Indiscreet	2	2	1	1	1	2
Individualistic	1	1	2	2	2	4
Indulgent	1	1	2	2	2	5
Industrious	1	1	2	2	2	7
Inefficient	2	2	1	1	1	3
Informal	1	1	2	2	2	5
Ingenious	1	1	2	2	2	5
Inhibited	2	2	1	1	1	6

Innovative	1	1	2	2	2	5
Inquisitive	1	1	2	2	2	4
Insecure	2	2	1	1	1	6
Insensitive	2	2	1	1	1	3
Insightful	1	1	2	2	2	5
Insincere	2	2	1	1	1	3
Intellectual	1	1	2	2	2	7
Intelligent	1	1	2	2	2	4
Intense	1	1	2	2	2	5
Intolerant	2	2	1	1	1	2
Introspective	1	1	2	2	2	5
Introverted	2	2	1	1	1	6
Intrusive	2	2	1	1	1	2
Inventive	1	1	2	2	2	5
Irreverent	2	2	1	1	1	2
Irritable	2	2	1	1	1	1
Jealous	1	1	1	1	1	1
Jovial	1	1	2	2	2	5
Kind	1	1	2	2	2	4
Knowledgeable	1	1	2	2	2	4
Lax	2	2	1	1	1	6
Lazy	2	2	1	1	1	2
Lenient	1	1	2	2	2	5
Lethargic	2	2	1	1	1	2
Logical	1	1	2	2	2	4
Loyal	1	1	2	2	2	4
Lustful	1	1	2	2	1	1
Magnetic	1	1	2	2	2	5
Manipulative	1	1	1	1	1	1
Mannerly	1	1	2	2	2	4
Masculine	2	2	1	1	4	1
Masochistic	2	2	1	1	1	3
Mature	1	1	2	2	2	4
Meddlesome	2	2	1	1	1	2
Meek	2	2	1	1	1	6
Melancholic	2	2	1	1	1	6
Merry	1	1	2	2	2	4
Meticulous	1	1	2	2	2	7
Mischievous	1	1	2	2	2	5
Modest	1	1	2	2	2	7
Moody	1	1	1	1	1	1
Moral	1	1	2	2	2	7
Moralistic	1	1	2	2	2	7
Naive	2	2	1	1	1	6
Natural	1	1	2	2	2	4

Negativistic	2	2	1	1	1	2
Negligent	2	2	1	1	1	2
Nervous	1	1	1	1	1	6
Nonchalant	1	1	2	2	2	5
Nonconforming	1	1	2	2	1	1
Nonpersistent	2	2	1	1	1	6
Nonreligious	2	2	1	1	1	1
Nosy	2	2	1	1	1	1
Objective	1	1	2	2	2	7
Obliging	1	1	2	2	2	4
Obsessive	2	2	1	1	1	1
Obstinate	1	1	1	1	1	1
Opinionated	1	1	2	2	2	5
Opportunistic	1	1	2	2	2	5
Optimistic	1	1	2	2	2	4
Orderly	1	1	2	2	2	7
Organized	1	1	2	2	2	7
Outspoken	1	1	2	2	1	5
Passionate	1	1	2	2	2	4
Passionless	2	2	1	1	1	3
Passive	2	2	1	1	1	6
Patient	1	1	2	2	2	7
Patronizing	2	2	1	1	1	1
Peaceful	1	1	2	2	2	4
Perceptive	1	1	2	2	2	4
Perfectionistic	1	1	2	2	2	7
Persistent	1	1	2	2	2	5
Pessimistic	2	2	1	1	1	2
Philosophical	1	1	2	2	2	5
Placid	2	2	1	1	1	6
Playful	1	1	2	2	2	4
Pleasant	1	1	2	2	2	4
Poised	1	1	2	2	2	7
Polite	1	1	2	2	2	4
Pompous	2	2	1	1	1	2
Possessive	1	1	1	1	1	5
Practical	1	1	2	2	2	7
Precise	1	1	2	2	2	7
Predictable	1	1	2	2	1	6
Prejudiced	2	2	1	1	1	2
Pretentious	2	2	1	1	1	1
Principled	1	1	2	2	2	4
Progressive	1	1	2	2	2	4
Prompt	1	1	2	2	2	7
Proud	1	1	2	2	2	4

Prudish	2	2	1	1	1	6
Punctual	1	1	2	2	2	7
Purposeful	1	1	2	2	2	4
Quarrelsome	2	2	1	1	1	2
Quiet	2	2	1	1	1	6
Rambunctious	1	1	2	2	2	5
Rash	2	2	1	1	1	2
Rational	1	1	2	2	2	4
Reasonable	1	1	2	2	2	4
Rebellious	1	1	1	1	1	1
Reckless	2	2	1	1	1	2
Refined	1	1	2	2	2	7
Relaxed	1	1	2	2	2	7
Reliable	1	1	2	2	2	4
Religious	1	1	2	2	2	6
Reserved	2	2	1	1	1	6
Respectful	1	1	2	2	2	4
Responsible	1	1	2	2	2	4
Restless	1	1	1	1	2	5
Restrained	2	2	1	1	1	6
Reverent	1	1	2	2	2	5
Rigid	2	2	1	1	1	2
Rough	2	2	1	1	1	2
Rude	2	2	1	1	1	3
Ruthless	2	2	1	1	1	3
Sarcastic	1	1	1	1	1	1
Scatterbrained	2	2	1	1	1	2
Scornful	2	2	1	1	1	2
Scrupulous	1	1	2	2	2	5
Secretive	2	2	1	1	1	6
Sedate	2	2	1	1	1	6
Self.Critical	1	1	2	2	2	4
Self.Disciplined	1	1	2	2	2	7
Self.Indulgent	1	1	2	2	2	5
Self.Pitying	2	2	1	1	1	2
Self.Seeking	1	1	2	2	2	5
Selfish	2	2	1	1	1	2
Selfless	2	2	1	1	1	6
Sensitive	1	1	2	2	2	4
Sensual	1	1	2	2	2	5
Sentimental	1	1	2	2	2	4
Serious	1	1	2	2	2	7
Sexy	1	1	2	2	2	5
Shallow	2	2	1	1	1	3
Shrewd	1	1	1	1	1	1

Shy	2	2	1	1	1	6
Silent	2	2	1	1	1	6
Simple	2	2	1	1	1	6
Sincere	1	1	2	2	2	4
Skeptical	1	1	1	1	1	1
Sloppy	2	2	1	1	1	2
Sluggish	2	2	1	1	1	3
Sly	1	1	1	1	1	1
Smart	1	1	2	2	2	4
Smug	2	2	1	1	1	2
Snobbish	2	2	1	1	1	2
Sociable	1	1	2	2	2	4
Social	1	1	2	2	2	4
Somber	2	2	1	1	1	6
Sophisticated	1	1	2	2	2	7
Spirited	1	1	2	2	2	4
Spontaneous	1	1	2	2	2	4
Steady	1	1	2	2	2	7
Stern	1	1	1	1	1	1
Stingy	2	2	1	1	1	2
Straightforward	1	1	2	2	2	4
Strict	2	2	1	1	1	1
Stubborn	1	1	2	2	2	5
Subjective	1	1	2	2	2	5
Submissive	2	2	1	1	1	6
Suggestible	1	1	2	2	2	5
Superstitious	2	2	1	1	1	2
Surly	2	2	1	1	1	2
Suspicious	1	1	1	1	1	1
Sympathetic	1	1	2	2	2	4
Systematic	1	1	2	2	2	7
Tactful	1	1	2	2	2	7
Tactless	2	2	1	1	1	3
Talkative	1	1	2	2	2	5
Temperamental	1	1	1	1	1	1
Tenacious	1	1	2	2	2	5
Thorough	1	1	2	2	2	7
Thoughtful	1	1	2	2	2	4
Thoughtless	2	2	1	1	1	3
Thrifty	1	1	2	2	2	7
Timid	2	2	1	1	1	6
Tolerant	1	1	2	2	2	4
Touchy	1	1	1	1	1	1
Tough	1	1	1	1	1	1
Traditional	1	1	2	2	2	7

Transparent	2	2	1	1	1	2
Trustful	1	1	2	2	2	4
Truthful	1	1	2	2	2	4
Unadventurous	2	2	1	1	1	3
Unaffectionate	2	2	1	1	1	3
Unaggressive	2	2	1	1	1	6
Unambitious	2	2	1	1	1	3
Unassuming	1	1	2	2	1	6
Uncharitable	2	2	1	1	1	3
Uncommunicative	2	2	1	1	1	3
Uncompetitive	2	2	1	1	1	6
Unconventional	1	1	2	2	1	1
Uncooperative	2	2	1	1	1	3
Uncouth	2	2	1	1	1	3
Undemanding	2	2	2	2	1	6
Undependable	2	2	1	1	1	3
Underhanded	2	2	1	1	1	3
Understanding	1	1	2	2	2	4
Unemotional	2	2	1	1	1	3
Unexcitable	2	2	1	1	1	3
Unforgiving	2	2	1	1	1	3
Unfriendly	2	2	1	1	1	3
Ungracious	2	2	1	1	1	3
Unimaginative	2	2	1	1	1	3
Uninhibited	1	1	2	2	1	5
Uninquisitive	2	2	1	1	1	3
Unintellectual	2	2	1	1	1	3
Unintelligent	2	2	1	1	1	3
Unkind	2	2	1	1	1	3
Unobservant	2	2	1	1	1	3
Unpredictable	1	1	1	1	1	1
Unreliable	2	2	1	1	1	3
Unrestrained	2	2	2	2	1	1
Unruly	2	2	1	1	1	2
Unscrupulous	2	2	1	1	1	2
Unselfish	1	1	2	2	2	5
Unsociable	2	2	1	1	1	3
Unsophisticated	2	2	1	1	1	2
Unstable	2	2	1	1	1	2
Unsympathetic	2	2	1	1	1	3
Vague	2	2	1	1	1	2
Vain	2	2	1	1	1	2
Verbal	1	1	2	2	2	5
Versatile	1	1	2	2	2	4
Vigorous	1	1	2	2	2	5

Vindictive	2	2	1	1	1	2
Vivacious	1	1	2	2	2	5
Volatile	2	2	1	1	1	1
Warm	1	1	2	2	2	4
Wary	1	1	1	1	1	1
Wasteful	2	2	1	1	1	2
Weariless	2	2	1	1	1	1
Wise	1	1	2	2	2	4
Wishy.Washy	2	2	1	1	1	2
Withdrawn	2	2	1	1	1	6
Witty	1	1	2	2	2	5
Wordy	2	2	1	1	1	1
Worldly	1	1	2	2	2	5
Zealous	1	1	2	2	2	5

Appendix D: Study 3 Heatmaps

Table 49. Accuracy Partial Eta Squared by Term Interaction

Term	**Adapt_bic_leiden**	**Adapt_bic_louvain**	**Adapt_bic_walktrap**	**EBICGLASSO_leiden**	**EBICGLASSO_louvain**	**EBICGLASSO_walktrap**	**Zero_leiden**	**Zero_louvain**	**Zero_walktrap**
factors	.17	.17	.13	.10	.08	.04	.03	.03	.04
total_variables	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample	.00	.00	.00	.00	.00	.00	.00	.00	.00
categories	.00	.00	.00	.00	.00	.00	.00	.00	.00
s_loading_range	.00	.00	.00	.00	.00	.00	.00	.00	.00
g_loading_range	.05	.05	.04	.02	.02	.04	.06	.06	.09
gender_prop	.00	.00	.00	.00	.00	.00	.00	.00	.00
prop_neg_general	.00	.00	.00	.00	.00	.00	.00	.00	.00
prop_neg_group	.00	.00	.00	.00	.00	.00	.00	.00	.00
prop_crossloading	.00	.00	.00	.00	.00	.00	.00	.00	.00
gender_effect_size	.00	.00	.00	.00	.00	.00	.00	.00	.00
skew_prop_vars	.00	.00	.00	.00	.00	.00	.00	.00	.00
skew_gamma_range	.00	.00	.00	.00	.00	.00	.00	.00	.00
skew_cases	.00	.00	.00	.00	.00	.00	.00	.00	.00
diff_prop_vars	.00	.00	.00	.00	.00	.00	.00	.00	.00
diff_shift	.00	.00	.00	.00	.00	.00	.00	.00	.00
factors:total_variables	.00	.00	.00	.00	.00	.00	.00	.00	.00
factors:sample	.00	.00	.00	.00	.00	.00	.00	.00	.00

factors:categories	.00	.00	.00	.00	.00	.00	.00	.00	.00
factors:s_loading_range	.00	.00	.00	.00	.00	.00	.00	.00	.00
factors:g_loading_range	.02	.02	.02	.01	.01	.00	.01	.01	.02
factors:gender_prop	.00	.00	.00	.00	.00	.00	.00	.00	.00
factors:prop_neg_general	.00	.00	.00	.00	.00	.00	.00	.00	.00
factors:prop_neg_group	.00	.00	.00	.00	.00	.00	.00	.00	.00
factors:prop_crossloading	.00	.00	.00	.00	.00	.00	.00	.00	.00
factors:gender_effect_size	.00	.00	.00	.00	.00	.00	.00	.00	.00
factors:skew_prop_vars	.00	.00	.00	.00	.00	.00	.00	.00	.00
factors:skew_gamma_range	.00	.00	.00	.00	.00	.00	.00	.00	.00
factors:skew_cases	.00	.00	.00	.00	.00	.00	.00	.00	.00
factors:diff_prop_vars	.00	.00	.00	.00	.00	.00	.00	.00	.00
factors:diff_shift	.00	.00	.00	.00	.00	.00	.00	.00	.00
total_variables:sample	.00	.00	.00	.00	.00	.00	.00	.00	.00
total_variables:categories	.00	.00	.00	.00	.00	.00	.00	.00	.00
total_variables:s_loading_range	.00	.00	.00	.00	.00	.00	.00	.00	.00
total_variables:g_loading_range	.00	.00	.00	.00	.00	.00	.00	.00	.00
total_variables:gender_prop	.00	.00	.00	.00	.00	.00	.00	.00	.00
total_variables:prop_neg_general	.00	.00	.00	.00	.00	.00	.00	.00	.00
total_variables:prop_neg_group	.00	.00	.00	.00	.00	.00	.00	.00	.00
total_variables:prop_crossloading	.00	.00	.00	.00	.00	.00	.00	.00	.00
total_variables:gender_effect_size	.00	.00	.00	.00	.00	.00	.00	.00	.00
total_variables:skew_prop_vars	.00	.00	.00	.00	.00	.00	.00	.00	.00
total_variables:skew_gamma_range	.00	.00	.00	.00	.00	.00	.00	.00	.00
total_variables:skew_cases	.00	.00	.00	.00	.00	.00	.00	.00	.00
total_variables:diff_prop_vars	.00	.00	.00	.00	.00	.00	.00	.00	.00
total_variables:diff_shift	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:categories	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:s_loading_range	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:g_loading_range	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:gender_prop	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:prop_neg_general	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:prop_neg_group	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:prop_crossloading	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:gender_effect_size	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:skew_prop_vars	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:skew_gamma_range	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:skew_cases	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:diff_prop_vars	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:diff_shift	.00	.00	.00	.00	.00	.00	.00	.00	.00
categories:s_loading_range	.00	.00	.00	.00	.00	.00	.00	.00	.00
categories:g_loading_range	.00	.00	.00	.00	.00	.00	.00	.00	.00
categories:gender_prop	.00	.00	.00	.00	.00	.00	.00	.00	.00
categories:prop_neg_general	.00	.00	.00	.00	.00	.00	.00	.00	.00
categories:prop_neg_group	.00	.00	.00	.00	.00	.00	.00	.00	.00

categories:prop_crossloading	.00	.00	.00	.00	.00	.00	.00	.00	.00
categories:gender_effect_size	.00	.00	.00	.00	.00	.00	.00	.00	.00
categories:skew_prop_vars	.00	.00	.00	.00	.00	.00	.00	.00	.00
categories:skew_gamma_range	.00	.00	.00	.00	.00	.00	.00	.00	.00
categories:skew_cases	.00	.00	.00	.00	.00	.00	.00	.00	.00
categories:diff_prop_vars	.00	.00	.00	.00	.00	.00	.00	.00	.00
categories:diff_shift	.00	.00	.00	.00	.00	.00	.00	.00	.00
s_loading_range:g_loading_range	.01	.01	.02	.00	.00	.01	.00	.00	.01
s_loading_range:gender_prop	.00	.00	.00	.00	.00	.00	.00	.00	.00
s_loading_range:prop_neg_general	.00	.00	.00	.00	.00	.00	.00	.00	.00
s_loading_range:prop_neg_group	.00	.00	.00	.00	.00	.00	.00	.00	.00
s_loading_range:prop_crossloading	.00	.00	.00	.00	.00	.00	.00	.00	.00
s_loading_range:gender_effect_size	.00	.00	.00	.00	.00	.00	.00	.00	.00
s_loading_range:skew_prop_vars	.00	.00	.00	.00	.00	.00	.00	.00	.00
s_loading_range:skew_gamma_range	.00	.00	.00	.00	.00	.00	.00	.00	.00
s_loading_range:skew_cases	.00	.00	.00	.00	.00	.00	.00	.00	.00
s_loading_range:diff_prop_vars	.00	.00	.00	.00	.00	.00	.00	.00	.00
s_loading_range:diff_shift	.00	.00	.00	.00	.00	.00	.00	.00	.00
g_loading_range:gender_prop	.00	.00	.00	.00	.00	.00	.00	.00	.00
g_loading_range:prop_neg_general	.00	.00	.00	.00	.00	.00	.00	.00	.00
g_loading_range:prop_neg_group	.00	.00	.00	.00	.00	.00	.00	.00	.00
g_loading_range:prop_crossloading	.00	.00	.00	.00	.00	.00	.00	.00	.00
g_loading_range:gender_effect_size	.00	.00	.00	.00	.00	.00	.00	.00	.00
g_loading_range:skew_prop_vars	.00	.00	.00	.00	.00	.00	.00	.00	.00
g_loading_range:skew_gamma_range	.00	.00	.00	.00	.00	.00	.00	.00	.00
g_loading_range:skew_cases	.00	.00	.00	.00	.00	.00	.00	.00	.00
g_loading_range:diff_prop_vars	.00	.00	.00	.00	.00	.00	.00	.00	.00
g_loading_range:diff_shift	.00	.00	.00	.00	.00	.00	.00	.00	.00
gender_prop:prop_neg_general	.00	.00	.00	.00	.00	.00	.00	.00	.00
gender_prop:prop_neg_group	.00	.00	.00	.00	.00	.00	.00	.00	.00
gender_prop:prop_crossloading	.00	.00	.00	.00	.00	.00	.00	.00	.00
gender_prop:gender_effect_size	.00	.00	.00	.00	.00	.00	.00	.00	.00
gender_prop:skew_prop_vars	.00	.00	.00	.00	.00	.00	.00	.00	.00
gender_prop:skew_gamma_range	.00	.00	.00	.00	.00	.00	.00	.00	.00
gender_prop:skew_cases	.00	.00	.00	.00	.00	.00	.00	.00	.00
gender_prop:diff_prop_vars	.00	.00	.00	.00	.00	.00	.00	.00	.00
gender_prop:diff_shift	.00	.00	.00	.00	.00	.00	.00	.00	.00
prop_neg_general:prop_neg_group	.00	.00	.00	.00	.00	.00	.00	.00	.00
prop_neg_general:prop_crossloading	.00	.00	.00	.00	.00	.00	.00	.00	.00
prop_neg_general:gender_effect_size	.00	.00	.00	.00	.00	.00	.00	.00	.00
prop_neg_general:skew_prop_vars	.00	.00	.00	.00	.00	.00	.00	.00	.00
prop_neg_general:skew_gamma_range	.00	.00	.00	.00	.00	.00	.00	.00	.00
prop_neg_general:skew_cases	.00	.00	.00	.00	.00	.00	.00	.00	.00
prop_neg_general:diff_prop_vars	.00	.00	.00	.00	.00	.00	.00	.00	.00
prop_neg_general:diff_shift	.00	.00	.00	.00	.00	.00	.00	.00	.00

prop_neg_group:prop_crossloading	.00	.00	.00	.00	.00	.00	.00	.00	.00
prop_neg_group:gender_effect_size	.00	.00	.00	.00	.00	.00	.00	.00	.00
prop_neg_group:skew_prop_vars	.00	.00	.00	.00	.00	.00	.00	.00	.00
prop_neg_group:skew_gamma_range	.00	.00	.00	.00	.00	.00	.00	.00	.00
prop_neg_group:skew_cases	.00	.00	.00	.00	.00	.00	.00	.00	.00
prop_neg_group:diff_prop_vars	.00	.00	.00	.00	.00	.00	.00	.00	.00
prop_neg_group:diff_shift	.00	.00	.00	.00	.00	.00	.00	.00	.00
prop_crossloading:gender_effect_size	.00	.00	.00	.00	.00	.00	.00	.00	.00
prop_crossloading:skew_prop_vars	.00	.00	.00	.00	.00	.00	.00	.00	.00
prop_crossloading:skew_gamma_range	.00	.00	.00	.00	.00	.00	.00	.00	.00
prop_crossloading:skew_cases	.00	.00	.00	.00	.00	.00	.00	.00	.00
prop_crossloading:diff_prop_vars	.00	.00	.00	.00	.00	.00	.00	.00	.00
prop_crossloading:diff_shift	.00	.00	.00	.00	.00	.00	.00	.00	.00
gender_effect_size:skew_prop_vars	.00	.00	.00	.00	.00	.00	.00	.00	.00
gender_effect_size:skew_gamma_range	.00	.00	.00	.00	.00	.00	.00	.00	.00
gender_effect_size:skew_cases	.00	.00	.00	.00	.00	.00	.00	.00	.00
gender_effect_size:diff_prop_vars	.00	.00	.00	.00	.00	.00	.00	.00	.00
gender_effect_size:diff_shift	.00	.00	.00	.00	.00	.00	.00	.00	.00
skew_prop_vars:skew_gamma_range	.00	.00	.00	.00	.00	.00	.00	.00	.00
skew_prop_vars:skew_cases	.00	.00	.00	.00	.00	.00	.00	.00	.00
skew_prop_vars:diff_prop_vars	.00	.00	.00	.00	.00	.00	.00	.00	.00
skew_prop_vars:diff_shift	.00	.00	.00	.00	.00	.00	.00	.00	.00
skew_gamma_range:skew_cases	.00	.00	.00	.00	.00	.00	.00	.00	.00
skew_gamma_range:diff_prop_vars	.00	.00	.00	.00	.00	.00	.00	.00	.00
skew_gamma_range:diff_shift	.00	.00	.00	.00	.00	.00	.00	.00	.00
skew_cases:diff_prop_vars	.00	.00	.00	.00	.00	.00	.00	.00	.00
skew_cases:diff_shift	.00	.00	.00	.00	.00	.00	.00	.00	.00
diff_prop_vars:diff_shift	.00	.00	.00	.00	.00	.00	.00	.00	.00

Table 50. MAE Partial Eta Squared by Term Interaction

Term	**Adapt_bic_leiden**	**Adapt_bic_louvain**	**Adapt_bic_walktrap**	**EBICGLASSO_leiden**	**EBICGLASSO_louvain**	**EBICGLASSO_walktrap**	**Zero_leiden**	**Zero_louvain**	**Zero_walktrap**
factors	.11	.11	.05	.03	.03	.01	.04	.04	.07
total_variables	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample	.00	.00	.00	.00	.00	.00	.00	.00	.00
categories	.00	.00	.00	.00	.00	.00	.00	.00	.00

s_loading_range	.00	.00	.00	.00	.00	.00	.00	.00	.00
g_loading_range	.02	.02	.01	.01	.01	.01	.02	.02	.04
gender_prop	.00	.00	.00	.00	.00	.00	.00	.00	.00
prop_neg_general	.00	.00	.00	.00	.00	.00	.00	.00	.00
prop_neg_group	.00	.00	.00	.00	.00	.00	.00	.00	.00
prop_crossloading	.00	.00	.00	.00	.00	.00	.00	.00	.00
gender_effect_size	.00	.00	.00	.00	.00	.00	.00	.00	.00
skew_prop_vars	.00	.00	.00	.00	.00	.00	.00	.00	.00
skew_gamma_range	.00	.00	.00	.00	.00	.00	.00	.00	.00
skew_cases	.00	.00	.00	.00	.00	.00	.00	.00	.00
diff_prop_vars	.00	.00	.00	.00	.00	.00	.00	.00	.00
diff_shift	.00	.00	.00	.00	.00	.00	.00	.00	.00
factors:total_variables	.00	.00	.00	.00	.00	.00	.00	.00	.00
factors:sample	.00	.00	.00	.00	.00	.00	.00	.00	.00
factors:categories	.00	.00	.00	.00	.00	.00	.00	.00	.00
factors:s_loading_range	.00	.00	.00	.00	.00	.00	.00	.00	.00
factors:g_loading_range	.01	.01	.00	.01	.01	.01	.01	.01	.01
factors:gender_prop	.00	.00	.00	.00	.00	.00	.00	.00	.00
factors:prop_neg_general	.00	.00	.00	.00	.00	.00	.00	.00	.00
factors:prop_neg_group	.00	.00	.00	.00	.00	.00	.00	.00	.00
factors:prop_crossloading	.00	.00	.00	.00	.00	.00	.00	.00	.00
factors:gender_effect_size	.00	.00	.00	.00	.00	.00	.00	.00	.00
factors:skew_prop_vars	.00	.00	.00	.00	.00	.00	.00	.00	.00
factors:skew_gamma_range	.00	.00	.00	.00	.00	.00	.00	.00	.00
factors:skew_cases	.00	.00	.00	.00	.00	.00	.00	.00	.00
factors:diff_prop_vars	.00	.00	.00	.00	.00	.00	.00	.00	.00
factors:diff_shift	.00	.00	.00	.00	.00	.00	.00	.00	.00
total_variables:sample	.00	.00	.00	.00	.00	.00	.00	.00	.00
total_variables:categories	.00	.00	.00	.00	.00	.00	.00	.00	.00
total_variables:s_loading_range	.00	.00	.00	.00	.00	.00	.00	.00	.00
total_variables:g_loading_range	.00	.00	.00	.00	.00	.00	.00	.00	.00
total_variables:gender_prop	.00	.00	.00	.00	.00	.00	.00	.00	.00
total_variables:prop_neg_general	.00	.00	.00	.00	.00	.00	.00	.00	.00
total_variables:prop_neg_group	.00	.00	.00	.00	.00	.00	.00	.00	.00
total_variables:prop_crossloading	.00	.00	.00	.00	.00	.00	.00	.00	.00
total_variables:gender_effect_size	.00	.00	.00	.00	.00	.00	.00	.00	.00
total_variables:skew_prop_vars	.00	.00	.00	.00	.00	.00	.00	.00	.00
total_variables:skew_gamma_range	.00	.00	.00	.00	.00	.00	.00	.00	.00
total_variables:skew_cases	.00	.00	.00	.00	.00	.00	.00	.00	.00
total_variables:diff_prop_vars	.00	.00	.00	.00	.00	.00	.00	.00	.00
total_variables:diff_shift	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:categories	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:s_loading_range	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:g_loading_range	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:gender_prop	.00	.00	.00	.00	.00	.00	.00	.00	.00

sample:prop_neg_general	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:prop_neg_group	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:prop_crossloading	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:gender_effect_size	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:skew_prop_vars	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:skew_gamma_range	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:skew_cases	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:diff_prop_vars	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:diff_shift	.00	.00	.00	.00	.00	.00	.00	.00	.00
categories:s_loading_range	.00	.00	.00	.00	.00	.00	.00	.00	.00
categories:g_loading_range	.00	.00	.00	.00	.00	.00	.00	.00	.00
categories:gender_prop	.00	.00	.00	.00	.00	.00	.00	.00	.00
categories:prop_neg_general	.00	.00	.00	.00	.00	.00	.00	.00	.00
categories:prop_neg_group	.00	.00	.00	.00	.00	.00	.00	.00	.00
categories:prop_crossloading	.00	.00	.00	.00	.00	.00	.00	.00	.00
categories:gender_effect_size	.00	.00	.00	.00	.00	.00	.00	.00	.00
categories:skew_prop_vars	.00	.00	.00	.00	.00	.00	.00	.00	.00
categories:skew_gamma_range	.00	.00	.00	.00	.00	.00	.00	.00	.00
categories:skew_cases	.00	.00	.00	.00	.00	.00	.00	.00	.00
categories:diff_prop_vars	.00	.00	.00	.00	.00	.00	.00	.00	.00
categories:diff_shift	.00	.00	.00	.00	.00	.00	.00	.00	.00
s_loading_range:g_loading_range	.02	.02	.01	.00	.00	.00	.00	.00	.00
s_loading_range:gender_prop	.00	.00	.00	.00	.00	.00	.00	.00	.00
s_loading_range:prop_neg_general	.00	.00	.00	.00	.00	.00	.00	.00	.00
s_loading_range:prop_neg_group	.00	.00	.00	.00	.00	.00	.00	.00	.00
s_loading_range:prop_crossloading	.00	.00	.00	.00	.00	.00	.00	.00	.00
s_loading_range:gender_effect_size	.00	.00	.00	.00	.00	.00	.00	.00	.00
s_loading_range:skew_prop_vars	.00	.00	.00	.00	.00	.00	.00	.00	.00
s_loading_range:skew_gamma_range	.00	.00	.00	.00	.00	.00	.00	.00	.00
s_loading_range:skew_cases	.00	.00	.00	.00	.00	.00	.00	.00	.00
s_loading_range:diff_prop_vars	.00	.00	.00	.00	.00	.00	.00	.00	.00
s_loading_range:diff_shift	.00	.00	.00	.00	.00	.00	.00	.00	.00
g_loading_range:gender_prop	.00	.00	.00	.00	.00	.00	.00	.00	.00
g_loading_range:prop_neg_general	.00	.00	.00	.00	.00	.00	.00	.00	.00
g_loading_range:prop_neg_group	.00	.00	.00	.00	.00	.00	.00	.00	.00
g_loading_range:prop_crossloading	.00	.00	.00	.00	.00	.00	.00	.00	.00
g_loading_range:gender_effect_size	.00	.00	.00	.00	.00	.00	.00	.00	.00
g_loading_range:skew_prop_vars	.00	.00	.00	.00	.00	.00	.00	.00	.00
g_loading_range:skew_gamma_range	.00	.00	.00	.00	.00	.00	.00	.00	.00
g_loading_range:skew_cases	.00	.00	.00	.00	.00	.00	.00	.00	.00
g_loading_range:diff_prop_vars	.00	.00	.00	.00	.00	.00	.00	.00	.00
g_loading_range:diff_shift	.00	.00	.00	.00	.00	.00	.00	.00	.00
gender_prop:prop_neg_general	.00	.00	.00	.00	.00	.00	.00	.00	.00
gender_prop:prop_neg_group	.00	.00	.00	.00	.00	.00	.00	.00	.00
gender_prop:prop_crossloading	.00	.00	.00	.00	.00	.00	.00	.00	.00

gender_prop:gender_effect_size	.00	.00	.00	.00	.00	.00	.00	.00	.00
gender_prop:skew_prop_vars	.00	.00	.00	.00	.00	.00	.00	.00	.00
gender_prop:skew_gamma_range	.00	.00	.00	.00	.00	.00	.00	.00	.00
gender_prop:skew_cases	.00	.00	.00	.00	.00	.00	.00	.00	.00
gender_prop:diff_prop_vars	.00	.00	.00	.00	.00	.00	.00	.00	.00
gender_prop:diff_shift	.00	.00	.00	.00	.00	.00	.00	.00	.00
prop_neg_general:prop_neg_group	.00	.00	.00	.00	.00	.00	.00	.00	.00
prop_neg_general:prop_crossloading	.00	.00	.00	.00	.00	.00	.00	.00	.00
prop_neg_general:gender_effect_size	.00	.00	.00	.00	.00	.00	.00	.00	.00
prop_neg_general:skew_prop_vars	.00	.00	.00	.00	.00	.00	.00	.00	.00
prop_neg_general:skew_gamma_range	.00	.00	.00	.00	.00	.00	.00	.00	.00
prop_neg_general:skew_cases	.00	.00	.00	.00	.00	.00	.00	.00	.00
prop_neg_general:diff_prop_vars	.00	.00	.00	.00	.00	.00	.00	.00	.00
prop_neg_general:diff_shift	.00	.00	.00	.00	.00	.00	.00	.00	.00
prop_neg_group:prop_crossloading	.00	.00	.00	.00	.00	.00	.00	.00	.00
prop_neg_group:gender_effect_size	.00	.00	.00	.00	.00	.00	.00	.00	.00
prop_neg_group:skew_prop_vars	.00	.00	.00	.00	.00	.00	.00	.00	.00
prop_neg_group:skew_gamma_range	.00	.00	.00	.00	.00	.00	.00	.00	.00
prop_neg_group:skew_cases	.00	.00	.00	.00	.00	.00	.00	.00	.00
prop_neg_group:diff_prop_vars	.00	.00	.00	.00	.00	.00	.00	.00	.00
prop_neg_group:diff_shift	.00	.00	.00	.00	.00	.00	.00	.00	.00
prop_crossloading:gender_effect_size	.00	.00	.00	.00	.00	.00	.00	.00	.00
prop_crossloading:skew_prop_vars	.00	.00	.00	.00	.00	.00	.00	.00	.00
prop_crossloading:skew_gamma_range	.00	.00	.00	.00	.00	.00	.00	.00	.00
prop_crossloading:skew_cases	.00	.00	.00	.00	.00	.00	.00	.00	.00
prop_crossloading:diff_prop_vars	.00	.00	.00	.00	.00	.00	.00	.00	.00
prop_crossloading:diff_shift	.00	.00	.00	.00	.00	.00	.00	.00	.00
gender_effect_size:skew_prop_vars	.00	.00	.00	.00	.00	.00	.00	.00	.00
gender_effect_size:skew_gamma_range	.00	.00	.00	.00	.00	.00	.00	.00	.00
gender_effect_size:skew_cases	.00	.00	.00	.00	.00	.00	.00	.00	.00
gender_effect_size:diff_prop_vars	.00	.00	.00	.00	.00	.00	.00	.00	.00
gender_effect_size:diff_shift	.00	.00	.00	.00	.00	.00	.00	.00	.00
skew_prop_vars:skew_gamma_range	.00	.00	.00	.00	.00	.00	.00	.00	.00
skew_prop_vars:skew_cases	.00	.00	.00	.00	.00	.00	.00	.00	.00
skew_prop_vars:diff_prop_vars	.00	.00	.00	.00	.00	.00	.00	.00	.00
skew_prop_vars:diff_shift	.00	.00	.00	.00	.00	.00	.00	.00	.00
skew_gamma_range:skew_cases	.00	.00	.00	.00	.00	.00	.00	.00	.00
skew_gamma_range:diff_prop_vars	.00	.00	.00	.00	.00	.00	.00	.00	.00
skew_gamma_range:diff_shift	.00	.00	.00	.00	.00	.00	.00	.00	.00
skew_cases:diff_prop_vars	.00	.00	.00	.00	.00	.00	.00	.00	.00
skew_cases:diff_shift	.00	.00	.00	.00	.00	.00	.00	.00	.00
diff_prop_vars:diff_shift	.00	.00	.00	.00	.00	.00	.00	.00	.00

Table 51. MBE Partial Eta Squared by Term Interaction

Term	Adapt_bic_leiden	Adapt_bic_louvain	Adapt_bic_walktrap	EBICGLASSO_leiden	EBICGLASSO_louvain	EBICGLASSO_walktrap	Zero_leiden	Zero_louvain	Zero_walktrap
factors	.11	.11	.05	.05	.06	.03	.07	.07	.09
total_variables	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample	.00	.00	.00	.00	.00	.00	.00	.00	.00
categories	.00	.00	.00	.00	.00	.00	.00	.00	.00
s_loading_range	.00	.00	.00	.00	.00	.00	.00	.00	.00
g_loading_range	.02	.02	.01	.01	.01	.00	.02	.02	.03
gender_prop	.00	.00	.00	.00	.00	.00	.00	.00	.00
prop_neg_general	.00	.00	.00	.00	.00	.00	.00	.00	.00
prop_neg_group	.00	.00	.00	.00	.00	.00	.00	.00	.00
prop_crossloading	.00	.00	.00	.00	.00	.00	.00	.00	.00
gender_effect_size	.00	.00	.00	.00	.00	.00	.00	.00	.00
skew_prop_vars	.00	.00	.00	.00	.00	.00	.00	.00	.00
skew_gamma_range	.00	.00	.00	.00	.00	.00	.00	.00	.00
skew_cases	.00	.00	.00	.00	.00	.00	.00	.00	.00
diff_prop_vars	.00	.00	.00	.00	.00	.00	.00	.00	.00
diff_shift	.00	.00	.00	.00	.00	.00	.00	.00	.00
factors:total_variables	.00	.00	.00	.00	.00	.00	.00	.00	.00
factors:sample	.00	.00	.00	.00	.00	.00	.00	.00	.00
factors:categories	.00	.00	.00	.00	.00	.00	.00	.00	.00
factors:s_loading_range	.00	.00	.00	.00	.00	.00	.00	.00	.00
factors:g_loading_range	.01	.01	.00	.02	.02	.01	.01	.01	.01
factors:gender_prop	.00	.00	.00	.00	.00	.00	.00	.00	.00
factors:prop_neg_general	.00	.00	.00	.00	.00	.00	.00	.00	.00
factors:prop_neg_group	.00	.00	.00	.00	.00	.00	.00	.00	.00
factors:prop_crossloading	.00	.00	.00	.00	.00	.00	.00	.00	.00
factors:gender_effect_size	.00	.00	.00	.00	.00	.00	.00	.00	.00
factors:skew_prop_vars	.00	.00	.00	.00	.00	.00	.00	.00	.00
factors:skew_gamma_range	.00	.00	.00	.00	.00	.00	.00	.00	.00
factors:skew_cases	.00	.00	.00	.00	.00	.00	.00	.00	.00
factors:diff_prop_vars	.00	.00	.00	.00	.00	.00	.00	.00	.00
factors:diff_shift	.00	.00	.00	.00	.00	.00	.00	.00	.00
total_variables:sample	.00	.00	.00	.00	.00	.00	.00	.00	.00
total_variables:categories	.00	.00	.00	.00	.00	.00	.00	.00	.00
total_variables:s_loading_range	.00	.00	.00	.00	.00	.00	.00	.00	.00
total_variables:g_loading_range	.00	.00	.00	.00	.00	.00	.00	.00	.00

total_variables:gender_prop	.00	.00	.00	.00	.00	.00	.00	.00	.00
total_variables:prop_neg_general	.00	.00	.00	.00	.00	.00	.00	.00	.00
total_variables:prop_neg_group	.00	.00	.00	.00	.00	.00	.00	.00	.00
total_variables:prop_crossloading	.00	.00	.00	.00	.00	.00	.00	.00	.00
total_variables:gender_effect_size	.00	.00	.00	.00	.00	.00	.00	.00	.00
total_variables:skew_prop_vars	.00	.00	.00	.00	.00	.00	.00	.00	.00
total_variables:skew_gamma_range	.00	.00	.00	.00	.00	.00	.00	.00	.00
total_variables:skew_cases	.00	.00	.00	.00	.00	.00	.00	.00	.00
total_variables:diff_prop_vars	.00	.00	.00	.00	.00	.00	.00	.00	.00
total_variables:diff_shift	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:categories	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:s_loading_range	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:g_loading_range	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:gender_prop	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:prop_neg_general	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:prop_neg_group	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:prop_crossloading	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:gender_effect_size	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:skew_prop_vars	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:skew_gamma_range	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:skew_cases	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:diff_prop_vars	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:diff_shift	.00	.00	.00	.00	.00	.00	.00	.00	.00
categories:s_loading_range	.00	.00	.00	.00	.00	.00	.00	.00	.00
categories:g_loading_range	.00	.00	.00	.00	.00	.00	.00	.00	.00
categories:gender_prop	.00	.00	.00	.00	.00	.00	.00	.00	.00
categories:prop_neg_general	.00	.00	.00	.00	.00	.00	.00	.00	.00
categories:prop_neg_group	.00	.00	.00	.00	.00	.00	.00	.00	.00
categories:prop_crossloading	.00	.00	.00	.00	.00	.00	.00	.00	.00
categories:gender_effect_size	.00	.00	.00	.00	.00	.00	.00	.00	.00
categories:skew_prop_vars	.00	.00	.00	.00	.00	.00	.00	.00	.00
categories:skew_gamma_range	.00	.00	.00	.00	.00	.00	.00	.00	.00
categories:skew_cases	.00	.00	.00	.00	.00	.00	.00	.00	.00
categories:diff_prop_vars	.00	.00	.00	.00	.00	.00	.00	.00	.00
categories:diff_shift	.00	.00	.00	.00	.00	.00	.00	.00	.00
s_loading_range:g_loading_range	.02	.02	.01	.00	.00	.00	.00	.00	.01
s_loading_range:gender_prop	.00	.00	.00	.00	.00	.00	.00	.00	.00
s_loading_range:prop_neg_general	.00	.00	.00	.00	.00	.00	.00	.00	.00
s_loading_range:prop_neg_group	.00	.00	.00	.00	.00	.00	.00	.00	.00
s_loading_range:prop_crossloading	.00	.00	.00	.00	.00	.00	.00	.00	.00
s_loading_range:gender_effect_size	.00	.00	.00	.00	.00	.00	.00	.00	.00
s_loading_range:skew_prop_vars	.00	.00	.00	.00	.00	.00	.00	.00	.00
s_loading_range:skew_gamma_range	.00	.00	.00	.00	.00	.00	.00	.00	.00
s_loading_range:skew_cases	.00	.00	.00	.00	.00	.00	.00	.00	.00
s_loading_range:diff_prop_vars	.00	.00	.00	.00	.00	.00	.00	.00	.00

s_loading_range:diff_shift	.00	.00	.00	.00	.00	.00	.00	.00	.00
g_loading_range:gender_prop	.00	.00	.00	.00	.00	.00	.00	.00	.00
g_loading_range:prop_neg_general	.00	.00	.00	.00	.00	.00	.00	.00	.00
g_loading_range:prop_neg_group	.00	.00	.00	.00	.00	.00	.00	.00	.00
g_loading_range:prop_crossloading	.00	.00	.00	.00	.00	.00	.00	.00	.00
g_loading_range:gender_effect_size	.00	.00	.00	.00	.00	.00	.00	.00	.00
g_loading_range:skew_prop_vars	.00	.00	.00	.00	.00	.00	.00	.00	.00
g_loading_range:skew_gamma_range	.00	.00	.00	.00	.00	.00	.00	.00	.00
g_loading_range:skew_cases	.00	.00	.00	.00	.00	.00	.00	.00	.00
g_loading_range:diff_prop_vars	.00	.00	.00	.00	.00	.00	.00	.00	.00
g_loading_range:diff_shift	.00	.00	.00	.00	.00	.00	.00	.00	.00
gender_prop:prop_neg_general	.00	.00	.00	.00	.00	.00	.00	.00	.00
gender_prop:prop_neg_group	.00	.00	.00	.00	.00	.00	.00	.00	.00
gender_prop:prop_crossloading	.00	.00	.00	.00	.00	.00	.00	.00	.00
gender_prop:gender_effect_size	.00	.00	.00	.00	.00	.00	.00	.00	.00
gender_prop:skew_prop_vars	.00	.00	.00	.00	.00	.00	.00	.00	.00
gender_prop:skew_gamma_range	.00	.00	.00	.00	.00	.00	.00	.00	.00
gender_prop:skew_cases	.00	.00	.00	.00	.00	.00	.00	.00	.00
gender_prop:diff_prop_vars	.00	.00	.00	.00	.00	.00	.00	.00	.00
gender_prop:diff_shift	.00	.00	.00	.00	.00	.00	.00	.00	.00
prop_neg_general:prop_neg_group	.00	.00	.00	.00	.00	.00	.00	.00	.00
prop_neg_general:prop_crossloading	.00	.00	.00	.00	.00	.00	.00	.00	.00
prop_neg_general:gender_effect_size	.00	.00	.00	.00	.00	.00	.00	.00	.00
prop_neg_general:skew_prop_vars	.00	.00	.00	.00	.00	.00	.00	.00	.00
prop_neg_general:skew_gamma_range	.00	.00	.00	.00	.00	.00	.00	.00	.00
prop_neg_general:skew_cases	.00	.00	.00	.00	.00	.00	.00	.00	.00
prop_neg_general:diff_prop_vars	.00	.00	.00	.00	.00	.00	.00	.00	.00
prop_neg_general:diff_shift	.00	.00	.00	.00	.00	.00	.00	.00	.00
prop_neg_group:prop_crossloading	.00	.00	.00	.00	.00	.00	.00	.00	.00
prop_neg_group:gender_effect_size	.00	.00	.00	.00	.00	.00	.00	.00	.00
prop_neg_group:skew_prop_vars	.00	.00	.00	.00	.00	.00	.00	.00	.00
prop_neg_group:skew_gamma_range	.00	.00	.00	.00	.00	.00	.00	.00	.00
prop_neg_group:skew_cases	.00	.00	.00	.00	.00	.00	.00	.00	.00
prop_neg_group:diff_prop_vars	.00	.00	.00	.00	.00	.00	.00	.00	.00
prop_neg_group:diff_shift	.00	.00	.00	.00	.00	.00	.00	.00	.00
prop_crossloading:gender_effect_size	.00	.00	.00	.00	.00	.00	.00	.00	.00
prop_crossloading:skew_prop_vars	.00	.00	.00	.00	.00	.00	.00	.00	.00
prop_crossloading:skew_gamma_range	.00	.00	.00	.00	.00	.00	.00	.00	.00
prop_crossloading:skew_cases	.00	.00	.00	.00	.00	.00	.00	.00	.00
prop_crossloading:diff_prop_vars	.00	.00	.00	.00	.00	.00	.00	.00	.00
prop_crossloading:diff_shift	.00	.00	.00	.00	.00	.00	.00	.00	.00
gender_effect_size:skew_prop_vars	.00	.00	.00	.00	.00	.00	.00	.00	.00
gender_effect_size:skew_gamma_range	.00	.00	.00	.00	.00	.00	.00	.00	.00
gender_effect_size:skew_cases	.00	.00	.00	.00	.00	.00	.00	.00	.00
gender_effect_size:diff_prop_vars	.00	.00	.00	.00	.00	.00	.00	.00	.00

gender_effect_size:diff_shift	.00	.00	.00	.00	.00	.00	.00	.00	.00
skew_prop_vars:skew_gamma_range	.00	.00	.00	.00	.00	.00	.00	.00	.00
skew_prop_vars:skew_cases	.00	.00	.00	.00	.00	.00	.00	.00	.00
skew_prop_vars:diff_prop_vars	.00	.00	.00	.00	.00	.00	.00	.00	.00
skew_prop_vars:diff_shift	.00	.00	.00	.00	.00	.00	.00	.00	.00
skew_gamma_range:skew_cases	.00	.00	.00	.00	.00	.00	.00	.00	.00
skew_gamma_range:diff_prop_vars	.00	.00	.00	.00	.00	.00	.00	.00	.00
skew_gamma_range:diff_shift	.00	.00	.00	.00	.00	.00	.00	.00	.00
skew_cases:diff_prop_vars	.00	.00	.00	.00	.00	.00	.00	.00	.00
skew_cases:diff_shift	.00	.00	.00	.00	.00	.00	.00	.00	.00
diff_prop_vars:diff_shift	.00	.00	.00	.00	.00	.00	.00	.00	.00

Table 52. ARI Partial Eta Squared by Term Interaction

Term	**Adapt_bic_leiden**	**Adapt_bic_louvain**	**Adapt_bic_walktrap**	**EBICGLASSO_leiden**	**EBICGLASSO_louvain**	**EBICGLASSO_walktrap**	**Zero_leiden**	**Zero_louvain**	**Zero_walktrap**
factors	.22	.22	.20	.19	.19	.17	.12	.11	.07
total_variables	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample	.00	.00	.00	.00	.00	.00	.00	.00	.00
categories	.00	.00	.00	.00	.00	.00	.00	.00	.00
s_loading_range	.00	.00	.00	.00	.00	.00	.00	.00	.00
g_loading_range	.03	.03	.04	.02	.02	.04	.05	.05	.08
gender_prop	.00	.00	.00	.00	.00	.00	.00	.00	.00
prop_neg_general	.00	.00	.00	.00	.00	.00	.00	.00	.00
prop_neg_group	.00	.00	.00	.00	.00	.00	.00	.00	.00
prop_crossloading	.00	.00	.00	.00	.00	.00	.00	.00	.00
gender_effect_size	.00	.00	.00	.00	.00	.00	.00	.00	.00
skew_prop_vars	.00	.00	.00	.00	.00	.00	.00	.00	.00
skew_gamma_range	.00	.00	.00	.00	.00	.00	.00	.00	.00
skew_cases	.00	.00	.00	.00	.00	.00	.00	.00	.00
diff_prop_vars	.00	.00	.00	.00	.00	.00	.00	.00	.00
diff_shift	.00	.00	.00	.00	.00	.00	.00	.00	.00
factors:total_variables	.00	.00	.00	.00	.00	.00	.00	.00	.00
factors:sample	.00	.00	.00	.00	.00	.00	.00	.00	.00
factors:categories	.00	.00	.00	.00	.00	.00	.00	.00	.00
factors:s_loading_range	.00	.00	.01	.01	.01	.01	.01	.01	.01
factors:g_loading_range	.02	.02	.02	.02	.02	.01	.01	.01	.00
factors:gender_prop	.00	.00	.00	.00	.00	.00	.00	.00	.00

factors:prop_neg_general	.00	.00	.00	.00	.00	.00	.00	.00	.00
factors:prop_neg_group	.00	.00	.00	.00	.00	.00	.00	.00	.00
factors:prop_crossloading	.00	.00	.00	.00	.00	.00	.00	.00	.00
factors:gender_effect_size	.00	.00	.00	.00	.00	.00	.00	.00	.00
factors:skew_prop_vars	.00	.00	.00	.00	.00	.00	.00	.00	.00
factors:skew_gamma_range	.00	.00	.00	.00	.00	.00	.00	.00	.00
factors:skew_cases	.00	.00	.00	.00	.00	.00	.00	.00	.00
factors:diff_prop_vars	.00	.00	.00	.00	.00	.00	.00	.00	.00
factors:diff_shift	.00	.00	.00	.00	.00	.00	.00	.00	.00
total_variables:sample	.00	.00	.00	.00	.00	.00	.00	.00	.00
total_variables:categories	.00	.00	.00	.00	.00	.00	.00	.00	.00
total_variables:s_loading_range	.00	.00	.00	.00	.00	.00	.00	.00	.00
total_variables:g_loading_range	.00	.00	.00	.00	.00	.00	.00	.00	.00
total_variables:gender_prop	.00	.00	.00	.00	.00	.00	.00	.00	.00
total_variables:prop_neg_general	.00	.00	.00	.00	.00	.00	.00	.00	.00
total_variables:prop_neg_group	.00	.00	.00	.00	.00	.00	.00	.00	.00
total_variables:prop_crossloading	.00	.00	.00	.00	.00	.00	.00	.00	.00
total_variables:gender_effect_size	.00	.00	.00	.00	.00	.00	.00	.00	.00
total_variables:skew_prop_vars	.00	.00	.00	.00	.00	.00	.00	.00	.00
total_variables:skew_gamma_range	.00	.00	.00	.00	.00	.00	.00	.00	.00
total_variables:skew_cases	.00	.00	.00	.00	.00	.00	.00	.00	.00
total_variables:diff_prop_vars	.00	.00	.00	.00	.00	.00	.00	.00	.00
total_variables:diff_shift	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:categories	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:s_loading_range	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:g_loading_range	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:gender_prop	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:prop_neg_general	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:prop_neg_group	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:prop_crossloading	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:gender_effect_size	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:skew_prop_vars	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:skew_gamma_range	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:skew_cases	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:diff_prop_vars	.00	.00	.00	.00	.00	.00	.00	.00	.00
sample:diff_shift	.00	.00	.00	.00	.00	.00	.00	.00	.00
categories:s_loading_range	.00	.00	.00	.00	.00	.00	.00	.00	.00
categories:g_loading_range	.00	.00	.00	.00	.00	.00	.00	.00	.00
categories:gender_prop	.00	.00	.00	.00	.00	.00	.00	.00	.00
categories:prop_neg_general	.00	.00	.00	.00	.00	.00	.00	.00	.00
categories:prop_neg_group	.00	.00	.00	.00	.00	.00	.00	.00	.00
categories:prop_crossloading	.00	.00	.00	.00	.00	.00	.00	.00	.00
categories:gender_effect_size	.00	.00	.00	.00	.00	.00	.00	.00	.00
categories:skew_prop_vars	.00	.00	.00	.00	.00	.00	.00	.00	.00
categories:skew_gamma_range	.00	.00	.00	.00	.00	.00	.00	.00	.00

categories:skew_cases	.00	.00	.00	.00	.00	.00	.00	.00	.00
categories:diff_prop_vars	.00	.00	.00	.00	.00	.00	.00	.00	.00
categories:diff_shift	.00	.00	.00	.00	.00	.00	.00	.00	.00
s_loading_range:g_loading_range	.01	.01	.01	.01	.01	.01	.01	.01	.01
s_loading_range:gender_prop	.00	.00	.00	.00	.00	.00	.00	.00	.00
s_loading_range:prop_neg_general	.00	.00	.00	.00	.00	.00	.00	.00	.00
s_loading_range:prop_neg_group	.00	.00	.00	.00	.00	.00	.00	.00	.00
s_loading_range:prop_crossloading	.00	.00	.00	.00	.00	.00	.00	.00	.00
s_loading_range:gender_effect_size	.00	.00	.00	.00	.00	.00	.00	.00	.00
s_loading_range:skew_prop_vars	.00	.00	.00	.00	.00	.00	.00	.00	.00
s_loading_range:skew_gamma_range	.00	.00	.00	.00	.00	.00	.00	.00	.00
s_loading_range:skew_cases	.00	.00	.00	.00	.00	.00	.00	.00	.00
s_loading_range:diff_prop_vars	.00	.00	.00	.00	.00	.00	.00	.00	.00
s_loading_range:diff_shift	.00	.00	.00	.00	.00	.00	.00	.00	.00
g_loading_range:gender_prop	.00	.00	.00	.00	.00	.00	.00	.00	.00
g_loading_range:prop_neg_general	.00	.00	.00	.00	.00	.00	.00	.00	.00
g_loading_range:prop_neg_group	.00	.00	.00	.00	.00	.00	.00	.00	.00
g_loading_range:prop_crossloading	.00	.00	.00	.00	.00	.00	.00	.00	.00
g_loading_range:gender_effect_size	.00	.00	.00	.00	.00	.00	.00	.00	.00
g_loading_range:skew_prop_vars	.00	.00	.00	.00	.00	.00	.00	.00	.00
g_loading_range:skew_gamma_range	.00	.00	.00	.00	.00	.00	.00	.00	.00
g_loading_range:skew_cases	.00	.00	.00	.00	.00	.00	.00	.00	.00
g_loading_range:diff_prop_vars	.00	.00	.00	.00	.00	.00	.00	.00	.00
g_loading_range:diff_shift	.00	.00	.00	.00	.00	.00	.00	.00	.00
gender_prop:prop_neg_general	.00	.00	.00	.00	.00	.00	.00	.00	.00
gender_prop:prop_neg_group	.00	.00	.00	.00	.00	.00	.00	.00	.00
gender_prop:prop_crossloading	.00	.00	.00	.00	.00	.00	.00	.00	.00
gender_prop:gender_effect_size	.00	.00	.00	.00	.00	.00	.00	.00	.00
gender_prop:skew_prop_vars	.00	.00	.00	.00	.00	.00	.00	.00	.00
gender_prop:skew_gamma_range	.00	.00	.00	.00	.00	.00	.00	.00	.00
gender_prop:skew_cases	.00	.00	.00	.00	.00	.00	.00	.00	.00
gender_prop:diff_prop_vars	.00	.00	.00	.00	.00	.00	.00	.00	.00
gender_prop:diff_shift	.00	.00	.00	.00	.00	.00	.00	.00	.00
prop_neg_general:prop_neg_group	.00	.00	.00	.00	.00	.00	.00	.00	.00
prop_neg_general:prop_crossloading	.00	.00	.00	.00	.00	.00	.00	.00	.00
prop_neg_general:gender_effect_size	.00	.00	.00	.00	.00	.00	.00	.00	.00
prop_neg_general:skew_prop_vars	.00	.00	.00	.00	.00	.00	.00	.00	.00
prop_neg_general:skew_gamma_range	.00	.00	.00	.00	.00	.00	.00	.00	.00
prop_neg_general:skew_cases	.00	.00	.00	.00	.00	.00	.00	.00	.00
prop_neg_general:diff_prop_vars	.00	.00	.00	.00	.00	.00	.00	.00	.00
prop_neg_general:diff_shift	.00	.00	.00	.00	.00	.00	.00	.00	.00
prop_neg_group:prop_crossloading	.00	.00	.00	.00	.00	.00	.00	.00	.00
prop_neg_group:gender_effect_size	.00	.00	.00	.00	.00	.00	.00	.00	.00
prop_neg_group:skew_prop_vars	.00	.00	.00	.00	.00	.00	.00	.00	.00
prop_neg_group:skew_gamma_range	.00	.00	.00	.00	.00	.00	.00	.00	.00

prop_neg_group:skew_cases	.00	.00	.00	.00	.00	.00	.00	.00	.00
prop_neg_group:diff_prop_vars	.00	.00	.00	.00	.00	.00	.00	.00	.00
prop_neg_group:diff_shift	.00	.00	.00	.00	.00	.00	.00	.00	.00
prop_crossloading:gender_effect_size	.00	.00	.00	.00	.00	.00	.00	.00	.00
prop_crossloading:skew_prop_vars	.00	.00	.00	.00	.00	.00	.00	.00	.00
prop_crossloading:skew_gamma_range	.00	.00	.00	.00	.00	.00	.00	.00	.00
prop_crossloading:skew_cases	.00	.00	.00	.00	.00	.00	.00	.00	.00
prop_crossloading:diff_prop_vars	.00	.00	.00	.00	.00	.00	.00	.00	.00
prop_crossloading:diff_shift	.00	.00	.00	.00	.00	.00	.00	.00	.00
gender_effect_size:skew_prop_vars	.00	.00	.00	.00	.00	.00	.00	.00	.00
gender_effect_size:skew_gamma_range	.00	.00	.00	.00	.00	.00	.00	.00	.00
gender_effect_size:skew_cases	.00	.00	.00	.00	.00	.00	.00	.00	.00
gender_effect_size:diff_prop_vars	.00	.00	.00	.00	.00	.00	.00	.00	.00
gender_effect_size:diff_shift	.00	.00	.00	.00	.00	.00	.00	.00	.00
skew_prop_vars:skew_gamma_range	.00	.00	.00	.00	.00	.00	.00	.00	.00
skew_prop_vars:skew_cases	.00	.00	.00	.00	.00	.00	.00	.00	.00
skew_prop_vars:diff_prop_vars	.00	.00	.00	.00	.00	.00	.00	.00	.00
skew_prop_vars:diff_shift	.00	.00	.00	.00	.00	.00	.00	.00	.00
skew_gamma_range:skew_cases	.00	.00	.00	.00	.00	.00	.00	.00	.00
skew_gamma_range:diff_prop_vars	.00	.00	.00	.00	.00	.00	.00	.00	.00
skew_gamma_range:diff_shift	.00	.00	.00	.00	.00	.00	.00	.00	.00
skew_cases:diff_prop_vars	.00	.00	.00	.00	.00	.00	.00	.00	.00
skew_cases:diff_shift	.00	.00	.00	.00	.00	.00	.00	.00	.00
diff_prop_vars:diff_shift	.00	.00	.00	.00	.00	.00	.00	.00	.00

Table 53. Varimax-Rotated Principal Components from Ipsatized Imputed Terms

Term	PC2	PC1	PC4	PC5	PC3
ACTIVE	0.056	0.279	**0.283**	0.014	0.241
AFFECTIONATE	**0.477**	0.376	-0.017	-0.056	0.006
ALERT	0.199	0.145	0.213	-0.185	**0.404**
ANIMATED	0.175	**0.532**	0.025	-0.167	0.065
ASSERTIVE	-0.161	**0.485**	0.224	-0.149	0.301
BIASED	**-0.291**	0.119	-0.090	0.215	0.162
BOLD	-0.264	**0.483**	0.274	-0.167	0.166
BRIGHT	0.033	0.115	0.148	**-0.416**	0.294
CALLOUS	**-0.572**	0.024	-0.054	0.023	0.032
CARELESS	-0.125	0.005	-0.071	-0.064	**-0.399**
CHATTY	0.187	**0.491**	-0.081	0.139	-0.084
CLEAR_HEADED	0.198	0.019	0.337	-0.169	**0.340**
COARSE	**-0.414**	0.107	0.054	-0.011	-0.166

COMPASSIONATE	**0.641**	0.139	-0.036	-0.113	-0.023
COMPULSIVE	-0.020	**0.263**	-0.220	-0.022	-0.102
CONSCIENTIOUS	0.318	-0.108	0.030	-0.060	**0.420**
CONSISTENT	0.174	-0.095	0.241	0.107	**0.451**
COOPERATATIVE	**0.520**	-0.049	0.125	0.038	0.220
COURTEOUS	**0.526**	0.054	0.101	0.006	0.243
CRAFTY	**-0.268**	0.214	0.046	-0.134	-0.027
CRANKY	-0.290	0.000	**-0.468**	-0.074	-0.003
CRUEL	**-0.333**	0.071	-0.051	0.089	-0.043
CULTURED	0.222	0.062	0.131	-0.276	**0.302**
CURT	**-0.391**	-0.001	-0.092	-0.070	0.116
DECEPTIVE	**-0.299**	0.055	-0.059	-0.108	-0.113
DEPRAVED	**-0.181**	0.016	0.030	0.113	-0.133
DIPLOMATIC	**0.369**	-0.017	0.169	-0.201	0.126
DISTRUSTFUL	-0.144	-0.195	**-0.207**	-0.156	-0.023
DRAMATIC	0.050	**0.514**	-0.111	-0.166	-0.018
EASY_GOING	0.328	-0.109	**0.353**	-0.017	-0.231
ELOQUENT	0.075	0.253	0.060	**-0.346**	0.207
ENVIOUS	-0.126	0.000	**-0.416**	-0.008	-0.032
ERRATIC	-0.142	0.131	-0.327	-0.079	**-0.407**
EVASIVE	-0.202	-0.077	-0.151	0.034	**-0.209**
EXHAUSTIBLE	0.172	-0.214	**-0.240**	0.084	-0.073
EXTRAVERTED	0.018	**0.640**	0.179	0.017	-0.003
FEARFUL	0.108	-0.122	**-0.536**	0.099	-0.090
FINICKY	-0.104	-0.011	**-0.316**	0.066	0.200
FORCEFUL	-0.308	0.313	0.123	-0.218	**0.320**
FRETFUL	-0.034	-0.063	**-0.580**	0.060	-0.010
GENEROUS	**0.488**	0.227	0.042	0.033	-0.012
GUILT_FREE	0.081	0.035	**0.530**	0.033	0.136
HAPHAZARD	-0.082	0.076	-0.104	-0.005	**-0.458**
HEADSTRONG	**-0.349**	0.267	-0.135	-0.099	0.135
HIGH_STRUNG	-0.141	0.261	**-0.440**	0.019	0.066
HUMORLESS	-0.023	**-0.248**	-0.023	0.229	0.117
IMAGINATIVE	0.121	0.203	0.061	**-0.451**	0.092
IMPRACTICAL	0.076	0.132	-0.161	-0.066	**-0.309**
INARTICULATE	0.050	-0.205	-0.036	**0.285**	-0.199
INHIBITED	0.107	**-0.435**	-0.309	0.057	0.025
INSECURE	0.107	-0.212	**-0.577**	-0.036	-0.183
INTROSPECTIVE	0.154	-0.163	-0.224	**-0.392**	0.026
IRREVERENT	-0.236	-0.051	0.013	**-0.491**	-0.147

JUVENILE	-0.121	0.090	-0.161	-0.166	**-0.358**
LEISURELY	0.192	-0.052	0.139	-0.034	**-0.259**
LENIENT	**0.307**	-0.092	0.136	-0.143	-0.161
LUSTFUL	-0.276	0.226	-0.088	**-0.281**	-0.145
MATERIALISTIC	**-0.174**	0.110	-0.158	-0.027	0.062
MOODY	-0.173	-0.093	**-0.558**	-0.091	-0.051
NARROW_MINDED	-0.231	-0.093	-0.168	**0.476**	0.135
NEAT	0.110	0.017	0.037	0.275	**0.367**
NONCONFORMING	-0.212	0.008	0.068	**-0.427**	-0.214
OBSTINATE	**-0.359**	0.025	-0.218	-0.101	-0.023
OPTIMISTIC	0.236	0.216	**0.491**	-0.016	0.034
OUTSTANDING	-0.026	0.252	**0.385**	-0.207	0.183
OVERRELAXED	0.036	-0.090	0.309	0.053	**-0.365**
PARTICULAR	-0.056	-0.003	-0.094	0.086	**0.374**
PASSIONLESS	-0.113	**-0.421**	0.122	0.219	-0.048
PHILOSOPHICAL	0.122	-0.049	-0.032	**-0.403**	-0.007
PLEASURE-LOVING	0.047	**0.203**	-0.030	-0.163	-0.186
POSSESSIVE	-0.229	0.045	**-0.268**	0.111	0.042
PREJUDICED	**-0.311**	-0.064	-0.083	0.273	0.107
PROGRESSIVE	0.079	0.156	0.183	**-0.324**	0.016
PURPOSEFUL	0.104	0.074	0.216	-0.031	**0.349**
REASONABLE	0.309	-0.205	**0.328**	-0.071	0.096
RELAXED	0.214	-0.039	**0.548**	0.029	-0.182
RESERVED	0.099	**-0.604**	-0.001	0.045	0.114
ROUGH	**-0.484**	0.052	0.161	-0.045	-0.114
RUN_DOWN	-0.053	-0.201	**-0.316**	0.064	-0.150
SECURE	0.120	0.110	**0.635**	0.114	0.141
SELF_CONTROLLED	**-0.225**	0.153	-0.079	-0.139	-0.145
SELF_PITYING	-0.096	0.034	**0.378**	-0.026	0.171
SENSUAL	0.007	**0.354**	0.094	-0.255	-0.079
SHALLOW	-0.197	-0.167	0.019	**0.341**	-0.261
SILENT	-0.001	**-0.633**	-0.002	0.028	-0.073
SLOPPY	-0.067	-0.173	-0.045	-0.134	**-0.463**
SOFT_SPOKEN	0.265	**-0.514**	0.139	0.026	-0.027
STIFF	-0.219	**-0.484**	-0.155	0.047	0.086
STUBBORN	**-0.327**	-0.054	-0.269	-0.013	0.050
SYMPATHETIC	**0.566**	0.043	-0.054	0.039	-0.154
TACTLESS	**-0.404**	0.019	-0.081	0.103	-0.123
TEMPERAMENTAL	-0.266	0.103	**-0.502**	0.041	-0.111
THOROUGH	0.031	-0.126	0.122	0.093	**0.486**

TIRED	0.056	-0.244	**-0.390**	0.086	-0.178
TRADITIONAL	0.105	-0.124	-0.029	**0.541**	0.236
UNADVENTUROUS	0.099	**-0.344**	-0.171	0.310	0.005
UNBIGOTED	**0.193**	-0.100	0.126	-0.137	-0.098
UNCOMPROMISING	**-0.270**	-0.077	0.032	0.079	0.083
UNCOUTH	**-0.346**	0.031	0.062	0.066	-0.306
UNDECEPTIVE	**0.228**	-0.097	0.131	-0.033	0.024
UNDERSTANDING	**0.509**	-0.056	0.137	-0.003	-0.073
UNEMOTIOL	-0.210	**-0.420**	0.393	0.064	0.055
UNEXTRAVERTED	0.073	**-0.372**	0.113	0.050	0.051
UNIMAGINATIVE	-0.025	-0.342	0.008	**0.468**	-0.101
UNINTELLIGENT	0.002	-0.095	0.078	**0.507**	-0.203
UNORTHODOX	-0.207	-0.039	0.085	**-0.468**	-0.282
UNPROGRESSIVE	-0.093	-0.296	-0.066	**0.363**	-0.106
UNSENSUAL	-0.029	**-0.443**	-0.020	0.251	-0.019
UNSTABLE	-0.147	-0.071	**-0.373**	0.089	-0.265
UNTALKATIVE	-0.098	**-0.657**	-0.036	0.011	-0.088
UNVARYING	-0.133	**-0.364**	0.019	0.219	0.084
UNYIELDING	**-0.367**	-0.177	-0.044	0.141	0.025
VICIOUS	**-0.317**	0.063	-0.014	0.177	-0.145
VULNERABLE	0.208	-0.024	**-0.399**	-0.035	-0.252
WELL_ADJUSTED	0.177	-0.003	**0.622**	0.086	0.155
WISE	0.083	0.003	**0.366**	-0.151	0.208
WITTY	0.002	**0.281**	0.196	-0.184	-0.012
ADAPTABLE	**0.290**	0.020	0.265	-0.237	0.050
AGGRESSIVE	-0.295	**0.475**	0.091	-0.013	0.246
AMBITIOUS	-0.021	**0.371**	0.149	0.015	0.348
ANXIOUS	0.020	-0.019	**-0.543**	0.104	0.094
ATTRACTIVE	0.130	**0.268**	0.098	-0.146	0.194
BIGOTED	**-0.278**	-0.048	-0.067	0.275	0.074
BRAVE	-0.007	0.216	**0.327**	-0.216	0.162
BULLHEADED	**-0.289**	0.175	-0.214	0.047	0.030
CALM	0.316	-0.207	**0.531**	-0.104	0.082
CASUAL	**0.218**	-0.145	0.184	-0.152	-0.179
CHEERFUL	**0.466**	0.260	0.347	0.038	0.002
CLIQUISH	-0.048	0.093	-0.074	**0.211**	0.053
COLD	-0.320	**-0.335**	-0.033	0.002	0.080
COMPETITIVE	-0.235	0.247	0.134	-0.001	**0.274**
CONFIDENT	-0.029	0.284	**0.554**	-0.110	0.348
CONSERVATIVE	0.036	-0.156	0.059	**0.494**	0.394

CONTENTED	0.295	0.025	**0.446**	0.137	0.120
COWARDLY	0.102	-0.179	**-0.280**	0.153	-0.134
CREATIVE	0.111	0.205	0.093	**-0.396**	0.141
CRUDE	**-0.399**	0.145	0.050	-0.068	-0.258
CUNNING	**-0.362**	0.170	0.079	-0.188	-0.041
DARING	-0.162	**0.362**	0.292	-0.262	0.056
DEEP	0.097	0.050	-0.082	**-0.409**	0.136
DEVOUT	0.237	0.118	-0.019	**0.373**	0.145
DISCRIMINATING	-0.037	-0.128	0.013	**-0.256**	0.205
DOWN_TO_EARTH	**0.326**	-0.063	0.117	-0.075	0.060
DULL	-0.021	**-0.521**	-0.164	0.120	-0.054
ECONOMIZING	0.169	-0.291	0.003	0.107	**0.352**
EMOTIONAL	0.281	0.307	**-0.477**	-0.002	-0.053
ETHICAL	**0.391**	-0.100	0.085	-0.064	0.278
EXACTING	-0.026	-0.035	-0.072	-0.041	**0.547**
EXCITABLE	0.046	**0.411**	-0.364	0.090	0.037
FATIGUELESS	-0.082	0.233	**0.415**	-0.040	0.114
FEMININE	**0.443**	0.065	-0.225	0.036	0.027
FLAWLESS	-0.045	0.086	**0.277**	0.107	0.262
FORMAL	0.054	0.042	0.118	0.106	**0.366**
FRUGAL	0.076	-0.289	0.046	0.088	**0.319**
GLUM	-0.136	**-0.391**	-0.375	-0.009	-0.024
GULLIBLE	**0.262**	0.048	-0.246	0.123	-0.170
HARDENED	**-0.443**	-0.108	-0.088	-0.144	0.046
HELPFUL	**0.469**	0.145	0.037	-0.027	0.140
HOMESPUN	0.257	-0.036	0.051	**0.285**	-0.008
HONEST	**0.372**	-0.052	0.102	0.075	0.307
IGNORANT	0.089	-0.072	-0.115	0.185	**-0.208**
IMMATURE	-0.127	0.000	-0.291	-0.001	**-0.317**
IMPRESSIVE	-0.034	**0.289**	0.168	-0.162	0.262
INCONSIDERATE	**-0.378**	-0.083	-0.029	-0.037	-0.095
INDEPENDENT	-0.026	0.109	0.249	**-0.266**	0.212
INEFFICIENT	0.082	-0.126	-0.121	-0.024	**-0.399**
INNOVATIVE	0.020	0.192	0.210	**-0.353**	0.131
INSINCERE	**-0.268**	-0.149	-0.033	0.017	-0.085
INTROVERTED	0.043	**-0.626**	-0.207	-0.232	-0.022
IRRITABLE	-0.300	-0.095	**-0.462**	-0.073	0.046
KIND	**0.580**	0.032	0.071	-0.020	0.069
LAZY	0.051	-0.195	-0.256	-0.109	**-0.390**
LIBERAL	0.238	0.011	0.020	**-0.485**	-0.242

MANIPULATIVE	-0.207	**0.208**	-0.147	-0.115	-0.005
MATURE	0.149	-0.134	**0.390**	0.118	0.297
MORAL	**0.325**	-0.105	0.171	0.317	0.252
NATIONALISTIC	0.030	0.045	0.155	**0.477**	0.211
NEGLIGENT	-0.141	-0.116	-0.111	0.034	**-0.423**
NONRELIGOUS	-0.194	-0.112	0.110	**-0.413**	-0.151
OLD_FASHIONED	0.094	-0.133	0.014	**0.444**	0.107
ORGANIZED	-0.025	-0.074	0.207	0.156	**0.485**
OVERPATIENT	**0.326**	-0.210	0.270	0.078	-0.108
OVERSENTIMENTAL	**0.316**	0.099	-0.232	0.200	-0.122
PASSIONATE	0.192	**0.445**	-0.063	-0.128	-0.092
POISED	0.085	0.118	0.265	-0.097	**0.285**
PRACTICAL	0.056	-0.258	0.239	0.098	**0.332**
PREJUDICELESS	**0.233**	-0.008	0.171	-0.136	-0.060
PROMPT	0.034	-0.117	0.124	0.163	**0.186**
QUIET	0.157	**-0.670**	0.020	-0.024	0.019
REBELLIOUS	-0.335	0.127	-0.150	**-0.395**	-0.218
RELIABLE	0.138	-0.144	0.155	0.161	**0.300**
REVERENT	0.243	0.009	0.000	**0.454**	0.108
RUDE	**-0.462**	0.010	0.012	-0.009	-0.173
RUTHLESS	**-0.463**	0.123	0.142	0.014	-0.105
SEDATE	0.176	**-0.470**	0.018	0.031	-0.003
SELF_ACTUALIZED	0.159	-0.240	**0.398**	0.036	0.260
SELF_SUFFICIENT	**-0.343**	-0.095	-0.242	-0.115	-0.057
SENTIMENTAL	**0.345**	0.149	-0.240	0.198	-0.053
SHORT_SIGHTED	-0.016	-0.038	-0.241	0.250	**-0.284**
SIMPLE	0.109	-0.143	-0.004	**0.333**	-0.169
SLICK	**-0.243**	0.139	0.111	0.067	-0.133
SOFT	**0.398**	-0.012	-0.152	0.163	-0.187
SOPHISTICATED	0.031	0.148	0.154	-0.213	**0.260**
STRAIT_LACED	0.050	-0.140	-0.021	**0.474**	0.271
SYSTEMATIC	-0.059	-0.127	0.139	0.097	**0.477**
TALKATIVE	0.079	**0.619**	0.022	0.141	-0.012
TENDER_MINDED	**0.522**	0.103	-0.173	0.195	-0.154
THRIFTY	0.070	**-0.302**	0.074	0.203	0.291
TOUCHY	-0.124	0.028	**-0.432**	0.088	0.007
TRUSTFUL	0.209	0.037	0.198	**0.267**	0.029
UNATTRACTIVE	0.003	**-0.312**	-0.107	0.182	-0.202
UNCHANGING	-0.131	-0.310	0.028	**0.332**	0.065
UNCONVENTIONAL	-0.185	0.048	0.095	**-0.457**	-0.326

UNCREATIVE	-0.003	-0.279	0.025	**0.382**	-0.139
UNDEMANDING	0.284	-0.260	0.240	0.178	**-0.299**
UNDEVOUT	-0.158	-0.150	0.147	**-0.360**	-0.132
UNENVIOUS	0.134	-0.113	**0.323**	-0.048	-0.092
UNFLUCTUATING	-0.166	-0.181	**0.222**	0.179	0.080
UNINQUISITIVE	0.029	-0.191	0.071	**0.508**	-0.095
UNKIND	**-0.396**	-0.158	0.059	0.214	-0.075
UNREFLECTIVE	-0.107	-0.122	0.209	**0.442**	-0.145
UNSEXUAL	0.017	**-0.323**	0.050	0.226	-0.061
UNSYMPATHETIC	**-0.474**	-0.175	0.213	0.190	0.003
UNTHRIFTY	-0.078	0.142	0.055	-0.022	**-0.355**
UNWILLFUL	0.144	**-0.256**	0.127	0.060	-0.187
VERBAL	-0.008	**0.435**	0.010	-0.126	0.054
VIGOROUS	-0.047	**0.376**	0.342	-0.038	0.180
WARM	**0.540**	0.320	0.128	0.102	-0.136
WICKED	**-0.287**	0.154	-0.045	-0.058	-0.230
WISHY_WASHY	0.093	-0.190	-0.214	0.077	**-0.324**
WORDY	0.008	**0.361**	-0.146	-0.044	-0.057
ADVENTUROUS	-0.004	**0.308**	0.251	-0.248	0.012
AGREEABLE	**0.530**	-0.065	0.093	-0.002	0.047
AMOROUS	0.186	**0.410**	0.003	-0.103	0.015
ARTISTIC	0.162	0.164	0.009	**-0.323**	-0.001
BASHFUL	0.164	**-0.509**	-0.196	-0.041	-0.025
BOISTEROUS	-0.230	**0.505**	0.024	-0.048	-0.148
BROAD_MINDED	0.305	0.026	0.153	**-0.483**	-0.043
BURNED_OUT	0.008	-0.183	**-0.408**	-0.007	-0.053
CAREFUL	0.312	-0.300	-0.032	0.126	**0.362**
CHANGEABLE	0.132	**0.221**	-0.140	-0.131	-0.107
CHOOSY	0.014	0.061	-0.196	-0.004	**0.338**
CLOSED_MINDED	-0.188	-0.090	-0.126	**0.438**	0.159
COMBATIVE	**-0.428**	0.203	-0.121	-0.019	0.067
COMPLEX	-0.072	0.016	-0.204	**-0.501**	0.145
CONFORMING	0.248	-0.137	-0.062	**0.387**	0.237
CONSIDERATE	**0.648**	0.001	0.024	0.016	0.129
CONVENTIONAL	0.275	-0.145	-0.011	**0.512**	0.287
COURAGEOS	0.104	0.261	**0.267**	-0.155	0.222
COY	0.035	0.097	0.004	**0.116**	0.054
CRITICAL	-0.322	-0.031	**-0.339**	-0.211	0.256
CULTIVATED	0.167	0.068	0.032	-0.258	**0.314**
CURIOUS	0.069	0.094	-0.021	**-0.465**	0.123

DECEITFUL	**-0.203**	0.083	-0.140	-0.057	-0.172
DEMANDING	**-0.406**	0.214	-0.235	-0.145	0.273
DIGNIFIED	0.164	0.072	0.064	-0.067	**0.434**
DISORGANIZED	0.104	0.016	-0.147	-0.130	**-0.446**
DOMINANT	-0.297	**0.369**	-0.020	-0.086	0.283
EARTHY	0.116	0.041	0.059	**-0.264**	-0.146
EFFICIENT	0.099	-0.009	0.206	0.007	**0.536**
ENERGETIC	0.059	0.332	**0.335**	-0.057	0.317
EROTIC	-0.095	0.334	-0.023	**-0.388**	-0.067
EXTRAVAGANT	-0.004	**0.403**	-0.029	-0.107	-0.078
FAULTFINDING	-0.349	0.035	**-0.384**	-0.028	0.180
FIRM	-0.100	0.085	0.134	-0.033	**0.456**
FOLKSY	**0.201**	0.041	0.087	0.086	-0.134
FREE_LIVING	-0.015	0.205	0.156	**-0.311**	-0.269
FUSSY	-0.155	0.046	-0.322	0.158	**0.330**
GREEDY	**-0.316**	0.075	-0.208	-0.042	-0.025
HALF_HEARTED	-0.084	**-0.317**	-0.224	0.034	-0.278
HARSH	**-0.444**	0.020	-0.206	-0.033	0.095
HELPLESS	0.143	-0.093	**-0.221**	0.173	-0.158
HUMOROUS	0.131	**0.289**	0.113	-0.235	-0.057
HYPOCRITICAL	-0.228	0.071	**-0.239**	0.109	-0.049
IMPOLITE	**-0.326**	-0.018	-0.022	-0.019	-0.100
IMPULSIVE	0.003	**0.306**	-0.130	-0.165	-0.255
INCONSISTENT	0.016	0.056	-0.321	-0.077	**-0.384**
INDIVIDUALISTIC	-0.095	0.077	0.120	**-0.416**	-0.022
INFORMAL	0.113	-0.150	0.043	-0.191	**-0.194**
INQUISITIVE	0.078	0.096	0.057	**-0.414**	0.113
INTELLECTUAL	0.166	0.056	0.046	**-0.442**	0.302
JEALOUS	-0.083	0.092	**-0.365**	-0.031	-0.015
LAID_BACK	0.172	-0.153	0.265	-0.121	**-0.366**
LAVISH	0.025	**0.350**	0.077	-0.113	-0.072
LOW_KEY	0.235	**-0.455**	0.206	-0.069	-0.154
MASCULINE	**-0.377**	-0.022	0.280	-0.232	0.001
MISERLY	-0.158	**-0.212**	-0.058	0.027	0.103
MORALISTIC	0.052	-0.036	-0.018	**0.483**	0.209
NATURAL	**0.240**	-0.064	0.216	-0.009	-0.083
NERVOUS	0.056	-0.094	**-0.535**	0.099	-0.036
OBEDIENT	0.274	-0.142	-0.012	**0.493**	0.146
OPPORTUNISTIC	-0.260	**0.266**	0.183	0.039	0.084
OUTSPOKEN	-0.275	**0.471**	0.062	-0.112	0.081

OVERCASUAL	-0.071	-0.109	0.082	0.034	**-0.350**
OVERTOLERANT	0.145	-0.132	0.053	0.096	**-0.328**
PATRIOTIC	0.074	0.033	0.135	**0.504**	0.188
PERFECTIONISTIC	-0.099	-0.002	-0.175	0.132	**0.440**
PLEASANT	**0.491**	0.072	0.223	0.132	-0.006
POLITE	**0.440**	-0.077	0.119	0.191	0.090
PREDICTABLE	0.230	-0.231	0.036	**0.375**	0.154
PRINCIPLED	0.242	-0.165	0.111	0.048	**0.244**
PRUDISH	0.045	-0.195	-0.123	**0.361**	0.148
RAMBUNCTIOUS	-0.176	**0.419**	0.103	-0.016	-0.168
REFINED	0.236	-0.021	0.101	0.018	**0.330**
RELIGIOUS	0.254	0.062	-0.054	**0.502**	0.131
RISQUE	-0.181	**0.293**	0.035	-0.267	-0.246
RUGGED	-0.320	0.106	**0.343**	-0.147	-0.048
SCHEMING	**-0.412**	0.200	0.018	-0.083	-0.137
SELF_INDULGENT	-0.079	-0.139	**-0.526**	0.079	-0.117
SENSITIVE	**0.409**	0.048	-0.283	-0.056	-0.119
SEXY	0.003	**0.341**	0.071	-0.189	0.034
SHY	0.149	**-0.576**	-0.185	-0.048	-0.066
SLEEPY	0.057	**-0.286**	-0.272	0.088	-0.252
SLY	**-0.361**	0.053	0.005	-0.063	-0.176
SOFT_HEARTED	**0.485**	-0.015	-0.167	0.142	-0.240
STEADY	0.254	-0.166	0.252	0.201	**0.271**
STRONG_WILLED	**-0.290**	0.197	-0.005	-0.053	0.226
SURLY	**-0.461**	0.104	-0.086	0.030	-0.055
TACTFUL	**0.434**	-0.098	0.185	-0.019	0.112
TASTEFUL	**0.381**	0.074	0.086	0.012	0.231
THEATRIC	0.032	**0.456**	-0.055	-0.141	-0.130
TIMID	0.210	**-0.500**	-0.255	0.095	-0.138
TOUGH	**-0.327**	0.140	0.178	-0.216	0.095
UNADAPTABLE	-0.145	-0.157	-0.156	**0.313**	-0.006
UNBIASED	**0.169**	-0.121	0.132	-0.150	-0.093
UNCHARITABLE	**-0.376**	-0.194	0.035	0.077	-0.093
UNCOOPERERATIVE	**-0.383**	-0.045	-0.028	0.001	-0.214
UNCRITICAL	**0.346**	-0.080	0.234	0.223	-0.225
UNDEPENDABLE	-0.045	-0.037	0.043	0.044	**-0.343**
UNDISCRIMINATING	0.146	-0.042	0.079	0.157	**-0.186**
UNEXCITABLE	0.012	**-0.441**	0.317	0.018	-0.072
UNFRUGAL	-0.062	0.163	0.041	-0.047	**-0.306**
UNINTELLECTUAL	-0.005	-0.116	0.106	**0.426**	-0.278

UNMORALIZING	-0.009	-0.123	0.137	-0.264	**-0.276**
UNPREDICTABLE	-0.136	0.128	0.017	-0.222	**-0.297**
UNRESTRAINED	-0.155	0.255	0.162	-0.133	**-0.290**
UNSOPHISTICATED	0.023	-0.245	-0.051	0.264	**-0.339**
UNSYSTEMATIC	0.071	-0.016	-0.041	0.035	**-0.558**
UNTIRING	-0.057	0.148	**0.362**	-0.033	-0.039
UNWORLDLY	0.143	-0.208	0.011	**0.352**	-0.127
VERSATILE	-0.006	0.146	**0.278**	-0.263	0.043
VOCAL	-0.118	**0.571**	0.033	-0.063	0.019
WILLFUL	**-0.322**	0.249	-0.069	-0.071	0.092
WITHDRAWN	-0.051	**-0.550**	-0.303	-0.115	-0.121
WORLDLY	-0.161	0.187	0.130	**-0.362**	0.062

Table 54. Cluster Solutions from Cluster and Factor Analyses

Term	**Zero-Order Boostrapped**	**EBICGLASSO Boostrapped**	**Adaptive Lasso Boostrapped**	**PC Boostrapped**
ACTIVE	1	1	1	3
AFFECTIONATE	2	2	2	1
ALERT	1	1	3	5
ANIMATED	3	3	4	2
ASSERTIVE	4	4	5	2
BIASED	5	5	6	1
BOLD	1	1	5	2
BRIGHT	6	6	7	4
CALLOUS	1	1	8	1
CARELESS	7	7	9	5
CHATTY	3	3	4	2
CLEAR_HEADED	8	1	3	5
COARSE	1	1	8	1
COMPASSIONATE	2	2	10	1
COMPULSIVE	9	8	11	2
CONSCIENTIOUS	10	7	12	5
CONSISTENT	10	7	12	5
COOPERATATIVE	2	2	13	1

COURTEOUS	2	2	14	1
CRAFTY	1	1	15	1
CRANKY	11	9	16	3
CRUEL	1	1	15	1
CULTURED	12	10	17	5
CURT	1	4	8	1
DECEPTIVE	1	1	15	1
DEPRAVED	1	1	15	1
DIPLOMATIC	2	2	13	1
DISTRUSTFUL	13	6	18	3
DRAMATIC	3	3	4	2
EASY_GOING	14	11	19	3
ELOQUENT	13	12	17	4
ENVIOUS	2	13	20	3
ERRATIC	15	8	21	5
EVASIVE	16	1	15	5
EXHAUSTIBLE	2	1	1	3
EXTRAVERTED	3	3	4	2
FEARFUL	2	2	22	3
FINICKY	10	14	23	3
FORCEFUL	4	4	5	5
FRETFUL	2	2	16	3
GENEROUS	2	2	10	1
GUILT_FREE	2	2	24	3
HAPHAZARD	7	7	9	5
HEADSTRONG	4	4	25	1
HIGH_STRUNG	17	15	16	3
HUMORLESS	13	16	4	2
IMAGINATIVE	13	6	26	4
IMPRACTICAL	7	17	9	5
INARTICULATE	13	12	7	4
INHIBITED	3	3	4	2
INSECURE	2	2	22	3
INTROSPECTIVE	13	6	27	4
IRREVERENT	13	18	6	4
JUVENILE	13	8	4	5
LEISURELY	14	11	19	5
LENIENT	14	11	14	1
LUSTFUL	18	19	28	4
MATERIALISTIC	18	20	20	1

MOODY	2	2	16	3
NARROW_MINDED	13	18	6	4
NEAT	10	7	23	5
NONCONFORMING	13	6	29	4
OBSTINATE	4	4	25	1
OPTIMISTIC	1	21	24	3
OUTSTANDING	1	1	30	3
OVERRELAXED	14	11	19	5
PARTICULAR	10	14	23	5
PASSIONLESS	17	19	28	2
PHILOSOPHICAL	13	6	27	4
PLEASURE-LOVING	19	19	28	2
POSSESSIVE	5	13	20	3
PREJUDICED	20	5	6	1
PROGRESSIVE	21	18	6	4
PURPOSEFUL	4	22	3	5
REASONABLE	17	23	31	3
RELAXED	14	11	32	3
RESERVED	3	3	4	2
ROUGH	1	1	8	1
RUN_DOWN	2	24	33	3
SECURE	2	2	24	3
SELF_CONTROLLED	18	20	20	1
SELF_PITYING	1	1	3	3
SENSUAL	18	19	28	2
SHALLOW	22	6	7	4
SILENT	3	3	4	2
SLOPPY	10	7	9	5
SOFT_SPOKEN	3	3	4	2
STIFF	23	3	4	2
STUBBORN	5	9	25	1
SYMPATHETIC	2	2	10	1
TACTLESS	24	25	34	1
TEMPERAMENTAL	2	9	16	3
THOROUGH	10	7	12	5
TIRED	2	24	1	3
TRADITIONAL	13	18	6	4
UNADVENTUROUS	18	26	35	2
UNBIGOTED	20	5	6	1
UNCOMPROMISING	10	27	36	1

UNCOUTH	1	1	15	1
UNDECEPTIVE	20	5	6	1
UNDERSTANDING	2	2	10	1
UNEMOTIOL	2	2	2	2
UNEXTRAVERTED	25	17	20	2
UNIMAGINATIVE	13	6	26	4
UNINTELLIGENT	13	6	7	4
UNORTHODOX	13	18	29	4
UNPROGRESSIVE	13	18	6	4
UNSENSUAL	18	19	28	2
UNSTABLE	2	2	10	3
UNTALKATIVE	3	3	4	2
UNVARYING	10	28	37	2
UNYIELDING	10	27	36	1
VICIOUS	1	1	15	1
VULNERABLE	2	2	10	3
WELL_ADJUSTED	2	2	24	3
WISE	1	29	38	3
WITTY	1	16	4	2
ADAPTABLE	26	30	19	1
AGGRESSIVE	1	22	5	2
AMBITIOUS	1	1	5	2
ANXIOUS	2	2	16	3
ATTRACTIVE	1	31	39	2
BIGOTED	20	5	6	1
BRAVE	1	1	40	3
BULLHEADED	4	4	25	1
CALM	17	15	32	3
CASUAL	14	11	19	1
CHEERFUL	14	32	41	1
CLIQUISH	20	33	6	4
COLD	27	34	42	2
COMPETITIVE	1	1	5	5
CONFIDENT	1	1	3	3
CONSERVATIVE	13	18	6	4
CONTENTED	2	2	24	3
COWARDLY	2	21	31	3
CREATIVE	13	6	26	4
CRUDE	1	1	15	1
CUNNING	1	1	15	1

DARING	1	1	40	2
DEEP	13	6	27	4
DEVOUT	13	18	6	4
DISCRIMINATING	12	6	18	4
DOWN_TO_EARTH	14	11	19	1
DULL	3	3	4	2
ECONOMIZING	25	17	43	5
EMOTIONAL	2	2	10	3
ETHICAL	10	28	44	1
EXACTING	10	14	12	5
EXCITABLE	17	15	16	2
FATIGUELESS	1	1	1	3
FEMININE	2	2	45	1
FLAWLESS	28	1	30	3
FORMAL	12	10	39	5
FRUGAL	25	17	43	5
GLUM	15	32	41	2
GULLIBLE	2	2	46	1
HARDENED	1	1	8	1
HELPFUL	2	2	10	1
HOMESPUN	13	18	19	4
HONEST	13	28	44	1
IGNORANT	2	12	7	5
IMMATURE	2	8	21	5
IMPRESSIVE	1	1	30	2
INCONSIDERATE	15	25	34	1
INDEPENDENT	1	1	3	4
INEFFICIENT	10	7	12	5
INNOVATIVE	21	35	26	4
INSINCERE	15	25	42	1
INTROVERTED	3	3	4	2
IRRITABLE	11	9	16	3
KIND	2	2	10	1
LAZY	14	7	1	5
LIBERAL	13	18	6	4
MANIPULATIVE	1	22	15	2
MATURE	27	8	38	3
MORAL	13	18	6	1
NATIONALISTIC	13	18	6	4
NEGLIGENT	10	7	9	5

NONRELIGOUS	13	18	6	4
OLD_FASHIONED	13	18	6	4
ORGANIZED	10	7	12	5
OVERPATIENT	17	36	47	1
OVERSENTIMENTAL	2	2	10	1
PASSIONATE	18	19	28	2
POISED	8	10	39	5
PRACTICAL	7	7	12	5
PREJUDICELESS	20	5	6	1
PROMPT	10	7	12	5
QUIET	3	3	4	2
REBELLIOUS	13	18	29	4
RELIABLE	10	7	12	5
REVERENT	13	18	6	4
RUDE	1	1	34	1
RUTHLESS	1	1	15	1
SEDATE	3	3	4	2
SELF_ACTUALIZED	23	15	38	3
SELF_SUFFICIENT	6	37	20	1
SENTIMENTAL	2	2	10	1
SHORT_SIGHTED	2	38	46	5
SIMPLE	13	6	7	4
SLICK	1	1	15	1
SOFT	2	2	10	1
SOPHISTICATED	8	10	39	5
STRAIT_LACED	13	18	6	4
SYSTEMATIC	10	7	12	5
TALKATIVE	3	3	4	2
TENDER_MINDED	2	2	10	1
THRIFTY	25	17	43	2
TOUCHY	2	2	16	3
TRUSTFUL	13	6	18	4
UNATTRACTIVE	1	19	28	2
UNCHANGING	13	18	37	4
UNCONVENTIONAL	13	6	29	4
UNCREATIVE	13	6	26	4
UNDEMANDING	4	4	48	5
UNDEVOUT	13	18	6	4
UNENVIOUS	20	18	6	3
UNFLUCTUATING	27	18	37	3

UNINQUISITIVE	13	6	26	4
UNKIND	2	2	42	1
UNREFLECTIVE	13	6	27	4
UNSEXUAL	18	19	28	2
UNSYMPATHETIC	2	2	10	1
UNTHRIFTY	25	17	43	5
UNWILLFUL	4	36	49	2
VERBAL	3	3	4	2
VIGOROUS	1	1	1	2
WARM	2	2	10	1
WICKED	18	1	15	1
WISHY_WASHY	2	2	10	5
WORDY	3	3	4	2
ADVENTUROUS	1	26	35	2
AGREEABLE	2	2	41	1
AMOROUS	18	19	28	2
ARTISTIC	13	6	26	4
BASHFUL	3	3	4	2
BOISTEROUS	24	3	4	2
BROAD_MINDED	13	18	6	4
BURNED_OUT	2	2	33	3
CAREFUL	25	23	4	5
CHANGEABLE	15	19	37	2
CHOOSY	10	14	23	5
CLOSED_MINDED	13	18	6	4
COMBATIVE	4	4	5	1
COMPLEX	13	6	27	4
CONFORMING	13	18	29	4
CONSIDERATE	2	2	10	1
CONVENTIONAL	13	18	29	4
COURAGEOS	1	1	40	3
COY	16	1	15	4
CRITICAL	5	9	7	3
CULTIVATED	12	10	17	5
CURIOUS	13	6	26	4
DECEITFUL	1	1	15	1
DEMANDING	4	4	5	1
DIGNIFIED	28	10	39	5
DISORGANIZED	10	7	12	5
DOMINANT	4	4	5	2

EARTHY	13	11	19	4
EFFICIENT	10	7	12	5
ENERGETIC	1	1	1	3
EROTIC	18	19	28	4
EXTRAVAGANT	9	17	20	2
FAULTFINDING	5	9	47	3
FIRM	5	4	5	5
FOLKSY	14	11	19	1
FREE_LIVING	13	39	50	4
FUSSY	10	14	23	5
GREEDY	1	22	20	1
HALF_HEARTED	2	40	14	2
HARSH	1	4	5	1
HELPLESS	2	41	22	3
HUMOROUS	21	16	4	2
HYPOCRITICAL	4	42	51	3
IMPOLITE	16	25	34	1
IMPULSIVE	25	17	11	2
INCONSISTENT	2	7	51	5
INDIVIDUALISTIC	13	6	29	4
INFORMAL	26	11	19	5
INQUISITIVE	13	6	26	4
INTELLECTUAL	13	6	7	4
JEALOUS	2	13	20	3
LAID_BACK	14	11	19	5
LAVISH	18	20	20	2
LOW_KEY	3	3	19	2
MASCULINE	1	1	45	1
MISERLY	25	17	43	2
MORALISTIC	13	18	6	4
NATURAL	14	11	19	1
NERVOUS	2	2	16	3
OBEDIENT	13	18	29	4
OPPORTUNISTIC	1	1	5	2
OUTSPOKEN	24	36	5	2
OVERCASUAL	14	11	19	5
OVERTOLERANT	2	2	14	5
PATRIOTIC	13	18	6	4
PERFECTIONISTIC	10	14	23	5
PLEASANT	2	2	10	1

POLITE	2	2	14	1
PREDICTABLE	13	18	29	4
PRINCIPLED	10	28	44	5
PRUDISH	13	18	6	4
RAMBUNCTIOUS	1	1	1	2
REFINED	12	10	39	5
RELIGIOUS	13	18	6	4
RISQUE	18	19	28	2
RUGGED	1	1	40	3
SCHEMING	1	1	15	1
SELF_INDULGENT	2	2	22	3
SENSITIVE	2	2	10	1
SEXY	18	19	28	2
SHY	3	3	4	2
SLEEPY	2	24	1	2
SLY	1	1	15	1
SOFT_HEARTED	2	2	10	1
STEADY	10	7	12	5
STRONG_WILLED	4	4	25	1
SURLY	1	1	8	1
TACTFUL	2	2	14	1
TASTEFUL	2	2	52	1
THEATRIC	3	16	4	2
TIMID	3	3	4	2
TOUGH	1	1	5	1
UNADAPTABLE	13	30	53	4
UNBIASED	20	5	6	1
UNCHARITABLE	2	2	53	1
UNCOOPERERATIVE	1	29	53	1
UNCRITICAL	5	9	48	1
UNDEPENDABLE	10	7	12	5
UNDISCRIMINATING	22	37	48	5
UNEXCITABLE	17	15	48	2
UNFRUGAL	25	17	43	5
UNINTELLECTUAL	13	6	7	4
UNMORALIZING	13	18	6	5
UNPREDICTABLE	13	18	29	5
UNRESTRAINED	21	39	4	5
UNSOPHISTICATED	8	10	39	5
UNSYSTEMATIC	10	7	12	5

UNTIRING	1	1	1	3
UNWORLDLY	6	43	6	4
VERSATILE	1	35	26	3
VOCAL	3	3	4	2
WILLFUL	4	4	5	1
WITHDRAWN	3	3	4	2
WORLDLY	18	19	28	4