₁ Investigating the Interaction between Associative, Semantic, and Thematic Database Norms

₂ for Memory Judgments and Retrieval

Abstract

This study examined the interactive relationship between semantic, thematic, and associative word pair strength in the prediction of item judgments and cued-recall performance. Participants were recruited from Amazon's Mechanical Turk and were given word pairs of varying relatedness to judge for their semantic, thematic, and associative strength. After completing a distractor task, participants then completed a cued recall task. First, we sought to expand previous work on judgments of associative memory (JAM) to include semantic and thematic based judgments, while also replicating bias and sensitivity findings. Next, we tested for an interaction between the three database norms (FSG, COS, and LSA) when predicting participant judgments and also extended previous work to test for interactions between the three database norms when predicting recall. Significant three-way interactions were found between FSG, COS, and LSA when predicting judgments and recall. For low semantic feature overlap, thematic and associative strength were competitive; as thematic strength increased, associative predictiveness decreased. However, this trend reversed for high semantic feature overlap, wherein thematic and associative strength were complementary as both set of simple slopes increased together. Overall, our findings indicate the degree to which the processing of associative, semantic, and thematic information impacts cognitive processes such as retrieval and item judgments, while also examining the underlying, interactive relationship that exists between these three types of information.

Keywords: judgments, memory, association, semantics, thematics

²⁴ Investigating the Interaction between Associative, Semantic, and Thematic Database Norms

²⁵ for Memory Judgments and Retrieval

²⁶ The study of cognition has a rich history of exploring the role of association in human

²⁷ memory. One key finding is that elements of cognitive processing play a critical role in how

²⁸ well an individual retains learned information. Throughout the mid-20th century, researchers

²⁹ investigated this notion, particularly through the use of paired-associate learning (PAL). In

³⁰ this paradigm, participants are presented with a pair of items and are asked to make

³¹ connections between them so that the presentation of one item (the cue) will in turn trigger

³² the recall of the other (the target). Early studies of this nature focused primarily on the

³³ effects of meaning and imagery on recall performance. For example, Smythe and Paivio

³⁴ (1968) found that noun imagery played a crucial role in PAL performance; subjects were

³⁵ much more likely to remember word-pairs that were low in meaning similarity if imagery

³⁶ between the two was high. Subsequent studies in this area focused on the effects of

³⁷ mediating variables on PAL tasks as well as the effects of imagery and meaningfulness on

³⁸ associative learning (Richardson, 1998), with modern studies shifting their focus towards a

³⁹ broad range of applied topics such as how PAL is affected by aging (Hertzog, Kidder,

⁴⁰ Powell-Moman, & Dunlosky, 2002), its impacts on second language acquisition (Chow, 2014),

⁴¹ and even in evolutionary psychology (Schwartz & Brothers, 2013).

⁴² Early PAL studies routinely relied on stimuli generated from word lists that focused

⁴³ extensively on measures of word frequency, concreteness, meaningfulness, and imagery

⁴⁴ (Paivio, 1969). However, the word pairs in these lists were typically created due to their

⁴⁵ apparent relatedness or frequency of occurrence in text. While lab self-generation appears

⁴⁶ face valid, one finds that this method of selection lacks a decisive method of defining the

⁴⁷ underlying relationships between the pairs (Buchanan, 2010), as these variables only capture

⁴⁸ psycholinguistic measurements of an individual concept (i.e., how concrete is *cat* and word

⁴⁹ occurrence). PAL is, by definition, used on word pairs, which requires examining concept

⁵⁰ relations in a reliable manner. As a result, free association norms have become a common

51 means of indexing associative strength between word pairs.

52   As we will use several related variables, it is important to first define association as the

53 context-based relation between concepts, usually found in text or popular culture (Nelson,

54 McEvoy, & Dennis, 2000). Such word associations typically arise through their co-occurrence

55 together in language. For example, the terms *peanut* and *butter* have become associated over

56 time through their joint use to depict a particular type of food, though separately, the two

57 concepts share very little in terms of meaning. To generate these norms, participants engage

58 in a free association task, in which they are presented with a cue word and are asked to list

59 the first related target word that comes to mind. The probability of producing a given

60 response to a particular cue word, or forward strength, can then be determined by dividing

61 the number of participants who produced the response in question by the total number of

62 responses generated for that word (FSG; Nelson et al., 2000). Using this technique,

63 researchers have developed databases of associative word norms that can be used to generate

64 stimuli with a high degree of reliability. Many of these databases are now readily available

65 online, with the largest one consisting of over 72,000 associates generated from more than

66 5,000 cue words (Nelson, McEvoy, & Schreiber, 2004). More recently, the Small World of

67 Words project (SWOW; De Deyne, Navarro, & Storms, 2013) has sought to capture

68 associations between Dutch words by employing a multiple response technique in contrast to

69 the traditional single response free association task used by Nelson et al. (2004). These

70 norms are now being collected for English words (De Deyne, Navarro, Perfors, Brysbaert, &

71 Storms, 2018).

72   Similar to association norms, semantic word norms provide researchers with another

73 option of constructing stimuli for use in word-pair tasks. These norms measure the

74 underlying concepts represented by words and allow researchers to tap into aspects of

75 semantic memory. Semantic memory is best described as an organized collection of our

76 general knowledge and contains information regarding a concept's meaning (Hutchison,

77 2003). Models of semantic memory broadly fall into one of two categories. Connectionist

78 models (e.g., Rogers & McClelland, 2006; Rumelhart, McClelland, & PDP Research Group,

79 1986) portray semantic memory as a system of interconnected units representing concepts,

80 which are linked together by weighted connections representing knowledge. By triggering the

81 input units, activation will then spread throughout the system activating or suppressing

82 connected units based on the weighted strength of the corresponding unit connections (Jones,

83 Willits, & Dennis, 2015). On the other hand, distributional models of semantic memory

84 posit that semantic representations are created through the co-occurrences of words together

85 in a body of text and suggest that words with similar meanings will appear together in

86 similar contexts (Riordan & Jones, 2011). Popular distributional models of semantic memory

87 include Latent Semantic Analysis (LSA; Landauer & Dumais, 1997) and the Hyperspace

88 Analogue to Language (HAL; Lund & Burgess, 1996).

89   Feature production tasks are a common means of producing semantic word norms

90 (Buchanan, Holmes, Teasley, & Hutchison, 2013; McRae, Cree, Seidenberg, & McNorgan,

91 2005; Vinson & Vigliocco, 2008) In such tasks, participants are shown the name of a concept

92 and are asked to list what they believe the concept's most important features to be (McRae

93 et al., 2005). Several statistical measures have been developed which measure the degree of

94 feature overlap between concepts. Similarity between any two concepts can be measured by

95 representing them as vectors and calculating the cosine value (COS) between them (Maki,

96 McKinley, & Thompson, 2004). Cosine values range from 0 (unrelated) to 1 (perfectly

97 related). For example, the pair *hornet - wasp* has a COS of .88, indicating a high degree of

98 overlap between the two concepts. Feature overlap can also be measured by JCN, which

99 involves calculating the information content value of each concept and the lowest

100 super-ordinate shared by each concept using an online dictionary, such as WordNET (Miller,

101 1995). The JCN value is then computed by summing together the difference of each concept

102 and its lowest super-ordinate (Jiang & Conrath, 1997; Maki et al., 2004). The advantage to

103 using COS values over JCN values is the limitation of JCN being tied to a somewhat static

104 dictionary database, while a semantic feature production task can be used on any concept to

105 calculate COS values. However, JCN values are less time consuming to obtain if both

106 concepts are in the database (Buchanan et al., 2013).

107   Semantic relations can be broadly described as being taxonomic or thematic in nature.

108 Whereas taxonomic relationships focus on the connections between features and concepts

109 within categories (e.g., *bird - pidgeon*), thematic relationships center around the links

110 between concepts and an overarching theme or scenario (e.g., *bird - nest*; Jones & Golonka,

111 2012). Jouravlev and McRae (2016) provide a list of 100 thematic relatedness production

112 norms, which were generated through a task similar to feature production in which

113 participants were presented with a concept and were asked to list names of other concepts

114 they believed to be related. Distributional models of semantic memory also lend themselves

115 well to the study of thematic word relations. Because these models are text-based and score

116 word pair relations in regard to their overall context within a document, they assess thematic

117 knowledge as well as semantic knowledge. Additionally, text-based models such as LSA are

118 able to account for both the effects of context and similarity of meaning, bridging the gap

119 between associations and semantics (Landauer, Foltz, Laham, Folt, & Laham, 1998).

120   Discussion of these measures then leads to the question of whether each one truly

121 assesses some unique concept or if they simply tap into our overall linguistic knowledge.

122 Taken at face value, word pair associations and semantic word relations appear to be vastly

123 different, yet the line between semantics/associations and thematics is much more blurred.

124 While thematic word relations are indeed an aspect of semantic memory and include word

125 co-occurrence as an integral part of their creation, themes also appear to be indicative of a

126 separate area of linguistic processing. Previous research by Maki and Buchanan (2008)

127 appears to confirm this theory. Using clustering and factor analysis techniques, they

128 analyzed multiple associative, semantic, and text-based measures of associative and semantic

129 knowledge. First, their findings suggested associative measures to be separate from semantic

130 measures. Additionally, semantic information derived from lexical measures (e.g., COS, JCN)

131 was found to be separate from measures generated from analysis of text corpora, suggesting

132 that text-based measures may be more representative of thematic information.

133 While it is apparent that these word relation measures are assessing different domains
134 of our linguistic knowledge, care must be taken when building experimental stimuli through
135 the use of normed databases, as many word pairs overlap on multiple types of measurements.
136 For example, some of the first studies on semantic priming used association word norms for
137 stimuli creation (Lucas, 2000; Meyer & Schvaneveldt, 1971; Meyer, Schvaneveldt, & Ruddy,
138 1975). This observation becomes strikingly apparent when one desires the creation of word
139 pairs related on only one dimension. One particular difficulty faced by researchers comes
140 when attempting to separate association strength from feature overlap, as highly associated
141 items tend to be semantically related as well. Additionally, a lack of association strength
142 between two items may not necessarily be indicative of a total lack of association, as
143 traditional norming tasks typically do not produce a large enough set of responses to capture
144 all available associations between items. Some items with extremely weak associations may
145 inevitably slip through the cracks (Hutchison, 2003). As such, the present study seeks to
146 provide further insight by examining how different levels of associative overlap (measured in
147 FSG), semantic overlap (feature overlap measured with COS), and thematic overlap
148 (measured with LSA) affect cognitive tasks such as short term item retrieval and item
149 relatedness judgments. Instead of focusing solely on one variable or trying to create stimuli
150 that represent only one form of relatedness, we included a range of each of these variables to
151 explore their potential interaction.

152 Specifically, this research was conceptualized within the framework of a three-tiered
153 view of the interconnections between these systems as it relates to processing concept
154 information. The three-tiered view is inspired by models of reading and naming, particularly
155 the triangle models presented by Seidenberg and McClelland (1989) and Plaut (1995). These
156 models explored the nature of reading as bidirectional relations between semantics,
157 orthography, and phonology. In this research, we examine if the associative, semantic, and
158 thematic systems are interactive for judgment and recall processes, much like the proposed

interactive nature of phonology, orthographics, and semantics for reading and naming

processes. Potentially, association, semantic, and thematic facets of word relation each

provide a unique contribution that can be judged and used for memory, thus, suggesting

three separate networks of independent information. This view seems unlikely, in that

research indicates that there is often overlap in the information provided by each measure of

word-pair relatedness. Instead, dynamic attractor networks, as proposed by Hopfield (1982)

and McLeod, Shallice, and Plaut (2000) may better represent the interplay between these

representations of concepts, as these models posit a similar feedback relationship between

concepts in a network. Using these models as a theoretical framework for our study, we

sought to understand how these three types of word-pair information may interact when

judgment and recall processes were applied to concept networks, and use it as a framework

for exploring how associative, semantic, and thematic memory networks share

interconnections. Therefore, this study provides evidence of the structure and interplay

between different forms of network relations for two cognitive tasks of judgment and retrieval

and will shed light on the underlying processing for each task.

Application to Judgment Studies

Traditional judgment of learning tasks (JOL) can be viewed as an application of the

PAL paradigm; participants are given pairs of items and are asked to judge how accurately

they would be able to correctly respond with the target with the cue on a recall task.

Judgments are typically made out of 100, with a participant response of 100 indicating full

confidence in recall ability. In their 2005 study, Koriat and Bjork examined overconfidence in

JOLs by manipulating associative relations (FSG) between word-pairs and found that

subjects were more likely to overestimate recall for pairs with little or no associative

relatedness. Additionally, this study found that when accounting for associative direction,

subjects were more likely to overestimate recall for pairs that were high in backwards

strength but low in forward strength. To account for this finding, the authors suggested that

JOLs may rely more heavily on overlap between cue and target with the direction of the associative relationship being secondary. Take for example the pair *feather - bird*, which has a FSG of .051 and a BSG of .359. This item pair also has a cosine value of .272 (suggesting low to moderate feature overlap) and an LSA score of .517 (suggesting moderate thematic overlap). As such, some of the overconfidence in JOLs may be attributed more than just item associations. Paired items may also be connected by similar themes or share certain features, resulting in inflated JOLs.

Expanding upon this research, the traditional judgment of learning task (JOL) can be manipulated to investigate perceptions of word pair relationships by having participants judge how related they believe the cue and target items to be (Maki, 2007a, 2007b). The judged values generated from this task can then be compared to the normed databases to create a similar accuracy function or correlation as is created in JOL studies. When presented with the item pair, participants are asked to estimate the number of people out of 100 who would provide the target word when shown only the cue (Maki, 2007b), which mimics how the association word norms are created through free association tasks. Maki (2007a) investigated such judgments within the context of associative memory by having participants rate how much associative overlap was shared between items and found that responses greatly overestimated the actual overlap strength for pairs that were weak associates, while underestimating strong associates; thus replicating the Koriat and Bjork (2005) findings for relatedness judgments based upon associative memory, rather than judgments based on learning.

The judgment of associative memory function (JAM) is created by plotting the judged values by the word pair's normed associative strength and calculating a fit line, which characteristically has a high intercept (bias) with a shallow slope (sensitivity). Figure 1 illustrates this function. Overall, the JAM function has been found to be highly reliable and generalized well across multiple variations of the study, with item characteristics such as word frequency, cue set size (QSS), and semantic similarity all having a minimal influence on

₂₁₂ it (Maki, 2007b). Furthermore, an applied meta-analysis of more than ten studies on JAM

₂₁₃ indicated that bias and sensitivity are nearly unchangeable, often hovering around 40-60

₂₁₄ points for the intercept and .20-.30 for the slope (Valentine & Buchanan, 2013). Additionally,

₂₁₅ Valentine and Buchanan (2013) extended this research to include judgments of semantic

₂₁₆ memory with the same results.

₂₁₇   The present study combined the paradigms of PAL, JOLs, and JAM to examine item

₂₁₈ recall and judgments for three types of judgments of relatedness (JORs) to explore the

₂₁₉ underlying memory network that is used for each of these cognitive processes as described

₂₂₀ above. We tested the following hypotheses based on previous research and semantic memory

₂₂₁ models:

₂₂₂ 1) First, we sought to expand previous Maki (2007b), Maki (2007a), Buchanan (2010),

₂₂₃   and Valentine and Buchanan (2013) research to include three types of JORs in one

₂₂₄   experiment, while replicating JAM bias and sensitivity findings. We used the three

₂₂₅   database norms for association, semantics, and thematics to predict each type of JOR

₂₂₆   and calculated average slope and intercept values for each participant. First, we

₂₂₇   expected to find slope and intercept values that were significantly different from zero.

₂₂₈   Though the three types of word relations are distinct from one another, we should

₂₂₉   expect to find slopes and intercepts for semantic and thematic JORs to be within the

₂₃₀   range of previous JAM findings if these memory systems are interconnected. Finally,

₂₃₁   we examined the frequency of each predictor being the strongest variable to predict its

₂₃₂   own judgment condition (i.e., how often association was the strongest predictor of

₂₃₃   associative JORs, etc.). This hypothesis explores if judgment findings replicate across a

₂₃₄   range of variables and covariates (rather than each individually, as previous JOL and

₂₃₅   JAM publications) and expands our knowledge on how the judgment process taps into

₂₃₆   the underlying memory network.

₂₃₇ 2) Next, we explored the predictions from semantic network models that the relation

₂₃₈   between association, semantics, and thematics would be bidirectional in nature (i.e.,

the three-tiered hypothesis of each type of knowledge stacked in memory). Therefore, we expected to find an interaction between database norms in predicting JORs. We used multilevel modeling to examine the interaction of database norms for association, semantics, and thematics in relation to participant judgments.

3) These analyses were then extended to recall as the dependent variable of interest. We tested for the interaction of database norms in predicting recall by using a multilevel logistic regression, while controlling for judgment condition and rating. We expected to find that database norms would show differences in recall based on the levels of other variables (the interaction would be significant), and that ratings would also positively predict recall (i.e., words that participants thought were more related would be remembered better). Because judgment and recall are different cognitive processes, we used this hypothesis to examine how memory networks may be differently interactive for memory in comparison to judgment.

4) Finally, we examined if the judgment slopes from Hypothesis 1 would be predictive of recall. Hypothesis 3 examined the direct relationship of word relatedness on recall, while this hypothesis explored if participant sensitivity to word relatedness was a predictor of recall. For this analysis, we used a multilevel logistic regression to control for multiple judgment slope conditions. This hypothesis combines both cognitive processes into one analysis, to explore how judgment ability (i.e., slopes) would impact the memory process.

Method

Participants

A power analysis was conducted using the *simR* package in *R* (Green & MacLeod, 2016). This package uses simulations to generate power estimates for mixed linear models created from the *lme4* package in *R* (Bates, Mächler, Bolker, & Walker, 2015). The results

264 of this analyses suggested a minimum of 35 participants would be required to detect an

265 effect. However, because power often tends to be underestimated, we extended participant

266 recruitment as funding permitted. In total, 112 participants took part in this study.

267 Participants were recruited from Amazon's Mechanical Turk, which is a website that allows

268 individuals to host projects and connects them with a large pool of respondents who

269 complete them for small amounts of money (Buhrmester, Kwang, & Gosling, 2011).

270 Participant responses were screened for a basic understanding of the study's instructions.

271 Responses were rejected for participants who entered related words when numerical

272 judgment responses were required, and for participants who responded to the cue words

273 during the recall phase with sentences or phrases instead of individual words. Those that

274 completed the study correctly were compensated $1.00 for their participation.

Materials

276   The stimuli used were sixty-three words pairs of varying associative, semantic, and

277 thematic relatedness which were created from the Buchanan et al. (2013) word norm

278 database and website. Associative relatedness was measured with Forward Strength (FSG),

279 which is the probability that a cue word will elicit a desired target word (Nelson et al., 2004).

280 This variable ranges from zero to one wherein zero indicates no association, while one

281 indicates that participants would always give a target word in response to the cue word.

282 Semantic relatedness was measured with cosine (COS), which is a measure of semantic

283 feature overlap (Buchanan et al., 2013; McRae et al., 2005; Vinson & Vigliocco, 2008). This

284 variable ranges from zero to one where zero indicates no shared semantic features between

285 concepts and higher numbers indicate more shared features between concepts. Thematic

286 relatedness was calculated with Latent Semantic Analysis (LSA), which generates a score

287 based upon the co-occurrences of words within a document (Landauer & Dumais, 1997;

288 Landauer et al., 1998). LSA values also range from zero to one, indicates no co-occurrence at

289 the low end and higher co-occurrence with higher values. These values were chosen to

290 represent these categories based on face validity and previous research on how word pair

291 psycholinguistic variables overlap (Maki & Buchanan, 2008).

292   The selected stimuli included a range of values for each variable. Table 1 displays

293 stimuli averages, SD, and ranges. A complete list of stimuli can be found at

294 http://osf.io/y8h7v. The stimuli were arranged into three blocks for each judgment

295 condition described below wherein each block contained 21 word pairs. Due to limitations of

296 the available stimuli, blocks were structured so that each one contained seven word pairs of

297 low (0-.33), medium (.34-.66), and high (.67-1.00) COS relatedness. Because of this selection

298 process, FSG and LSA strengths are contingent upon the selected stimuli's COS strengths.

299 We selected stimuli within the cosine groupings to cover a range of FSG and LSA values, but

300 certain combinations are often difficult to achieve. For example, there are only four

301 word-pairs that are both high COS and high FSG, thus limiting the ability to manipulate

302 LSA. The study was built online using Qualtrics, and three surveys were created to

303 counter-balance the order in which judgment conditions appeared. Each word pair appeared

304 counter-balanced across each judgment condition, and stimuli were randomized within each

305 block.

Procedure

307   The present study was divided into three phases. In the first phase, JORs were elicited

308 by presenting participants with word pairs and asking them to make judgments of how

309 related they believed the words in each pair to be. This judgment phase consisted of three

310 blocks of 21 word pairs which corresponded to one of three types of word pair relationships:

311 associative, semantic, or thematic. Each block was preceded by a set of instructions

312 explaining one of the three types of relationships, and participants were provided with

313 examples which illustrated the type of relationship to be judged. Participants were then

314 presented with the word pairs to be judged. The associative block began by explaining

315 associative memory and the role of free association tasks. Participants were provided with

examples of both strong and weak associates. For example, *lost* and *found* and were
presented as an example of a strongly associated pair, while *article* was paired with
newspaper, *the*, and *clothing* to illustrate that words can have many weak associates. The
semantic judgment block provided participants with a brief overview of how words are
related by meaning and showed examples of concepts with both high and low feature overlap.
Tortoise and *turtle* were provided as an example of two concepts with significant overlap.
Other examples were then provided to illustrate concepts with little or no overlap. For the
thematic judgments, participants were provided with an explanation of thematic relatedness.
Tree is explained to be related to *leaf*, *fruit*, and *branch*, but not *computer*. Participants were
then given three concepts (*lost*, *old*, *article*) and were asked to come up with words that they
feel are thematically related.

After viewing the examples at the start of the block, participants completed the JOR
task. Each block contained a set of instructions which were contingent upon the type of JOR
being elicited. For example, instructions in the associative block asked participants to
estimate how many individuals out of 100 they expect would respond to the cue word with a
given target, instructions for semantic JORs asked participants to indicate the percent of
features shared between two concepts, and instructions for the thematic JOR task asked
participants to base ratings on how likely to words would be used together in the same story.
The complete experiment can be found at http://osf.io/y8h7v, which contains the exact
instructions given to participants for each block and displays the structure of the study. All
instructions were modeled after Buchanan (2010) and Valentine and Buchanan (2013).

In accordance with previous work on JOLs and JAM, participants made JOR ratings
using a scale of zero to one hundred, with zero indicating no relationship, and one hundred
indicating a perfect relationship. Participants typed their responses into the survey. Once
completed, participants then completed the remaining judgment blocks in the same manner.
Each subsequent judgment block changed the type of JOR being made. Three versions of
the study were created, which counter-balanced the order in which the judgment blocks

appeared, and participants were randomly assigned to a survey version. This resulted in each

word pair receiving a relatedness judgments on each of the three types relationships.

After completing the judgment phase, participants were then presented with a short

distractor task to account for recency effects. In this section, participants were presented

with a randomized list of the fifty U.S. states and were asked to arrange them in alphabetical

order. This task was timed to last two minutes. Once time had elapsed, participants

automatically progressed to the final phase, which consisted of a cued-recall task.

Participants were presented with each of the 63 cue words from the judgment phase and

were asked to complete each word pair by responding with the correct target word.

Participants were informed that they would not be penalized for guessing. The cued-recall

task included all stimuli in a random order.

Results

Data Processing and Descriptive Statistics

First, the results from the recall phase of the study was coded as zero for incorrect

responses, one for correct responses, and NA for participants who did not complete the recall

section (all or nearly all responses were blank). All word responses to judgment items were

deleted and set to missing data. The final dataset was created by splitting the initial data

file into six sections (one for each of the three experimental blocks and their corresponding

recall scores). Each section was individually melted using the *reshape* package in *R*

(Wickham, 2007) and was written as a csv file. The six output files were then combined to

form the final dataset. Code is available on our OSF page embedded inline with the

manuscript in an *R* markdown document written with the *papaja* package (Aust & Barth,

2017). With 112 participants, the dataset in long format included 7,056 rows of potential

data (i.e., 112 participants * 63 JORs). One out of range JOR data point (> 100) was

corrected to NA. Missing data for JORs or recall were then excluded from the analysis,

which included word responses to judgment items (i.e., responding with *cat* instead of a

369 number). These items usually excluded a participant from receiving Amazon Mechanical

370 Turk payment, but were included in the datasets found online. In total, 787 data points were

371 excluded (188 JOR only, 279 recall only, 320 both), leading to a final *N* of 105 participants

372 and 6,269 observations. Recall and JOR values were then screened for outliers using

373 Mahalanobis distance at $p < .001$, and no outliers were found (Tabachnick & Fidell, 2012).

374 To screen for multicollinearity, we examined correlations between judgment items, COS,

375 LSA, and FSG. All correlations were rs $< .50$.

376   The mean JOR for the associative condition ($M = 58.74$, $SD = 30.28$) was lower than

377 the semantic ($M = 66.98$, $SD = 28.31$) and thematic ($M = 71.96$, $SD = 27.80$) conditions.

378 Recall averaged over 60% for all three conditions: associative $M = 63.40$, $SD = 48.18$;

379 semantic $M = 68.02$, $SD = 46.65$; thematic $M = 64.89$, $SD = 47.74$.

Hypothesis 1

381   Our first hypothesis sought to replicate bias and sensitivity findings from previous

382 research while expanding the JAM function to include judgments based on three types of

383 memory. FSG, COS, and LSA were used to predict each type of relatedness judgment. JOR

384 values were divided by 100, so as to place them on the same scale as the database norms.

385 Slopes and intercepts were then calculated for each participant's ratings for each of the three

386 JOR conditions, as long as they contained at least nine data points out of the twenty-one

387 that were possible. Single sample *t*-tests were then conducted to test if slope and intercept

388 values significantly differed from zero. See Table 2 for means and standard deviations. Slopes

389 were then compared to the JAM function, which is characterized by high intercepts (between

390 40 and 60 on a 100 point scale) and shallow slopes (between 20 and 40). Because of the

391 scaling of our data, to replicate this function, we should expect to find intercepts ranging

392 from .40 to .60 and slopes in the range of 0.20. to 0.40. Intercepts for associative, semantic,

393 and thematic JORs were each significant, and all fell within or near the expected range.

394 Overall, thematic JORs had the highest intercept at .656, while JORs elicited in the

395 associative condition had the lowest intercept at .511.

396   The JAM slope was successfully replicated for FSG in the associative JOR condition,
397 with FSG significantly predicting association, although the slope was slightly higher than
398 expected at .491. COS and LSA did not significantly predict association. For semantic
399 judgments, each of the three database norms were significant predictors. However, JAM
400 slopes were not replicated for this judgment type, as FSG had the highest slope at .118,
401 followed by LSA .085, and then COS .059. These findings were mirrored for thematic JORs,
402 as each database norm was a significant predictor, yet slopes for each predictor fell below
403 range of the expected JAM slopes. Again, FSG had the highest slope, this time just out of
404 range at .192, followed closely by LSA at .188. Interestingly, COS slopes were found to be
405 negative for this judgment condition, -.081. Overall, although JAM slopes were not
406 successfully replicated in each JOR condition, the high intercepts and shallow slopes present
407 across conditions are still indicative of overconfidence and insensitivity in participant JORs.

408   Additionally, we examined the frequency that each predictor variable was the strongest
409 predictor for each of the three JOR conditions. For the associative condition, FSG was the
410 strongest predictor for 64.0% of the participants, with COS and LSA being the strongest for
411 only 16.0% and 20.0% of participants respectively. These differences were less distinct when
412 examining the semantic and thematic JOR conditions. In the semantic condition, FSG was
413 highest at 44.1% of participants, LSA was second at 32.4%, and COS was least likely at
414 23.5%. Finally, in the thematic condition, LSA was most likely to be the strongest predictor
415 with 44.6% of participants, with FSG being the second most likely at 36.6%, and COS again
416 being least likely at 18.8%. Interestingly, in all three conditions, COS was least likely to be
417 the strongest predictor, even in the semantic condition. Therefore, these results provide
418 evidence of the nature of judgments on the memory network as each judgment type appeared
419 to tap each tier differently, suggesting a three-part system, rather than one large,
420 encompassing memory network.

Hypothesis 2

The goal of Hypothesis 2 was to test for an interaction between the three database norms when predicting participant JORs to examine the bidirectional network model. First, the database norms were mean centered to control for multicollinearity. The *nlme* package and *lme* function were used to calculate these analyses (Pinheiro, Bates, Debroy, Sarkar, & Team, 2017). A maximum likelihood multilevel model was used to test the interaction between FSG, COS, and LSA when predicting JOR values, with participant number used as the random intercept factor. The type of JOR being elicited was controlled for, so as to better assess the impact of each word overlap measure regardless of JOR condition. Multilevel models were used to retain all data points (rather than averaging over items and conditions) while controlling for correlated error due to participants, which makes these models advantageous for multiway repeated measures designs (Gelman, 2006). This analysis resulted in a significant three-way interaction between FSG, COS, and LSA ($\beta = 3.324$, $p < .001$), which is examined below in a simple slopes analysis. Table 3 includes values for main effects, two-way, and three-way interactions.

To investigate this interaction, simple slopes were calculated for low, average, and high levels of COS. This variable was chosen for two reasons: first, it was found to be the weakest of the three predictors in hypothesis one, and second, manipulating COS would allow us to track changes across FSG and LSA. Significant two-way interactions were found between FSG and LSA at both low COS ($\beta = -1.492$, $p < .001$), average COS ($\beta = -0.569$, $p < .001$), and high COS ($\beta = 0.355$, $p = .013$). A second level was then added to the analysis in which simple slopes were created for each level of LSA, allowing us to assess the effects of LSA at different levels of COS on FSG. When both COS and LSA were low, FSG significantly predicted JOR values ($\beta = 0.663$, p $< .001$). At low COS and average LSA, FSG decreased but still significantly predicted JORs ($\beta = 0.375$, p $< .001$). However, when COS was low and LSA was high, FSG was not a significant predictor ($\beta = 0.087$, p $= .079$). A similar set of results was found at the average COS level. When COS was average and LSA was LOW,

FSG was a significant predictor, ($\beta = 0.381$, $p < .001$). As LSA increased at average COS

levels, FSG decreased in strength: average COS, average LSA FSG ($\beta = 0.355$, p .013) and

average COS, high LSA FSG ($\beta = 0.161$, $p < .001$). This finding suggests that at low COS,

LSA and FSG create a seesaw effect in which increasing levels of thematics is

counterbalanced by decreasing importance of association when predicting JORs. FSG was

not a significant predictor when COS was high and LSA was low (0.099, p = .088). At high

COS and average LSA, FSG significantly predicted JORs ($\beta = 0.167$, p < .001), and finally

when both COS and LSA were high, FSG increased and was a significant predictor of JOR

values ($\beta = 0.236$, p < .001). Thus, at high levels of semantic overlap, associative and

thematic overlap are complementary when predicting JOR ratings, increasing together as

semantic strength increases. Figure 2 displays the three-way interaction wherein the top row

of figures indicates the seesaw effect, as thematic strength increases, the predictive ability of

associative overlap decreases in strength. The bottom row indicates the complementary

effect where increases in LSA occur with increases in FSG predictor strength. Therefore, the

cognitive process of judgment appears to be interactive in nature across these three types of

memory information.

Hypothesis 3

Given the results of Hypothesis 2, we then sought to extend the analysis to participant

recall scores. A multilevel logistic regression was used with the *lme4* package and *glmer()*

function (Pinheiro et al., 2017), testing the interaction between FSG, COS, and LSA when

predicting participant recall. As with the previous hypothesis, we controlled for JOR

condition and, additionally, covaried JOR ratings. Participants were used as a random

intercept factor. Judged values were a significant predictor of recall, ($\beta = 0.686$, $p < .001$)

where increases in judged strength predicted increases in recall. A significant three-way

interaction was detected between FSG, COS, and LSA ($\beta = 24.572$, $p < .001$). See Table 4

for main effects, two-way, and three-way interaction values.

474   The same moderation process used in Hypothesis 2 was then repeated, with simple

475   slopes first calculated at low, average, and high levels of COS. This set of analyses resulted

476   in significant two-way interactions between LSA and FSG at low COS (β = -7.845, p < .001)

477   and high COS (β = 5.811, p = .009). No significant two-way interaction was found at

478   average COS (β = -1.017, p = .493). Following the design of hypothesis two, simple slopes

479   were then calculated for low, average, and high levels of LSA at the low and high levels of

480   COS, allowing us to assess how FSG effects recall at varying levels of both COS and LSA.

481   When both COS and LSA were low, FSG was a significant predictor of recall (β = 4.116, p

482   < .001). At low COS and average LSA, FSG decreased from both low levels, but was still a

483   significant predictor (β = 2.601, p < .001), and finally, low COS and high LSA, FSG was the

484   weakest predictor of the three (β = 1.086, p = .030). As with Hypothesis 2, LSA and FSG

485   counterbalanced one another, wherein the increasing levels of thematics led to a decrease in

486   the importance of association in predicting recall. At high COS and low LSA, FSG was a

487   significant predictor (β = 2.447, p = .003). When COS was high and LSA was average, FSG

488   increased as a predictor and remained significant (β = 3.569, p < .001). This finding

489   repeated when both COS and LSA were high, with FSG increasing as a predictor of recall (β

490   = 4.692, p < .001). Therefore, at high levels of at high levels of semantics, thematics and

491   association are complementary predictors of recall, increasing together and extending the

492   findings of Hypothesis 2 to participant recall. Figure 3 displays the three-way interaction.

493   The top left figure indicates the counterbalancing effect of recall of LSA and FSG, while the

494   top right figure shows no differences in simple slopes for average levels of cosine. The bottom

495   left figure indicates the complementary effects where LSA and FSG increase together as

496   predictors of recall at high COS levels.

Hypothesis 4

498   In our fourth and final hypothesis, we investigated whether the JOR slopes and

499   intercepts obtained in Hypothesis 1 would be predictive of recall ability. Whereas Hypothesis

500 3 indicated that word relatedness was directly related to recall performance, this hypothesis

501 instead looked at whether or not participants' sensitivity and bias to word relatedness could

502 be used a predictor of recall (Maki, 2007b). This analysis was conducted with a multilevel

503 logistic regression, as described in Hypothesis 3, where each database slope and intercept was

504 used as predictors of recall using participant as a random intercept factor. These analyses

505 were separated by judgment condition, so that each set of JOR slopes and intercepts were

506 used to predict recall. The separation controlled for the number of variables in the equation,

507 as all slopes and intercepts would have resulted in overfitting. These values were obtained

508 from Hypothesis 1 where each participant's individual slopes and intercepts were calculated

509 for associative, semantic, and thematic JOR conditions. Table 2 shows average slopes and

510 intercepts for recall for each of the three types of memory, and Table 5 portrays the

511 regression coefficients and statistics. In the associative condition, FSG slope significantly

512 predicted recall ($b = 0.898$, $p = .008$), while COS slope ($b = 0.314$, $p = .568$) and LSA slope

513 ($b = 0.501$, $p = .279$) were non-significant. In the semantic condition, COS slope ($b = 2.039$,

514 $p < .001$) and LSA slope ($b = 1.061$, $p = .020$) were both found to be significant predictors

515 of recall. FSG slope was non-significant in this condition ($b = 0.381$, $p = .187$). Finally, no

516 predictors were significant in the thematic condition, though LSA slope was found to be the

517 strongest ($b = 0.896$, $p = .090$). This analysis indicated the extent to which the cognitive

518 processes are related to each other as part of the memory network (i.e., judgment sensitivity

519 predicting recall), furthering Hypothesis 2 and 3 which illustrated the nature of those

520 cognitive processes' relationship with the underlying memory network.

Discussion

522   This study investigated the relationship between associative, semantic, and thematic

523 word relations and their effect on participant JORs and recall performance through the

524 testing of four hypotheses. In our first hypothesis, bias and sensitivity findings first proposed

525 by Maki (2007a) were successfully replicated in the associative condition, with slope and

intercept values falling within the expected range. While these findings were not fully replicated when extending the analysis to include semantic and thematic JORs (as slopes in these conditions did not fall within the appropriate range), participants still displayed high intercepts and shallow slopes, suggesting overconfidence in judgment making and an insensitivity to changes in strength between pairs. Additionally, when looking at the frequency that each predictor was the strongest in making JORs, FSG was the best predictor for both the associative and semantic conditions, while LSA was the best predictor in the thematic condition. In each of the three conditions, COS was the weakest predictor, even when participants were asked to make semantic judgments. This finding suggests that associative relationships seem to take precedence over semantic relationships when judging pair relatedness, regardless of what type of JOR is being elicited. Additionally, this finding may be taken as further evidence of a separation between associative information and semantic information, in which associative information is always processed, while semantic information may be suppressed due to task demands (Buchanan, 2010; Hutchison & Bosco, 2007).

Our second hypothesis examined the three-way interaction between FSG, COS, and LSA when predicting participant JORs. At low semantic overlap, a seesaw effect was found in which increases in thematic strength led to decreases in associative predictiveness. This finding was then replicated in Hypothesis 3 when extending the analysis to predict recall. By limiting the semantic relationships between pairs, an increased importance is placed on the role of associations and thematics when making relatedness judgments or retrieving pairs. In such cases, increasing the amount of thematic overlap between pairs results in thematic relationships taking precedent over associative relationships. However, when semantic overlap was high, a complementary relationship was found in which increases in thematic strength in turn led to increases in the strength of FSG as a predictor. This result suggests that at high semantic overlap, associations and thematic relations build upon one another. Because thematics is tied to both semantic overlap and item associations, the presence of

strong thematic relationships between pairs during conditions of high semantic overlap boosts the predictive ability of associative word norms for both recall and JORs.

Finally, our fourth hypothesis used the JOR slopes and intercepts calculated in Hypothesis 1 to investigate if participants' bias and sensitivity to word relatedness could be used to predict recall. For the associative condition, the FSG slope significantly predicted recall. In the semantic condition, recall was significantly predicted by both the COS and LSA slopes, with COS being the strongest. However, for the thematic condition, although the LSA slope was the strongest, no predictors were significant. One explanation for this finding is that thematic relationships between item pairs act as a blend between associations and semantics. As such, LSA faces increased competition from the associative and semantic database norms when predicting recall in this manner. Additionally, the dominance of FSG when predicting recall in the associative condition may be attributed to word associations being more accessible (and, thus, easier to process) than semantic or thematic relations between pairs.

Overall, our findings indicated the degree to which the processing of associative, semantic, and thematic information impacts retrieval and judgment making tasks and the interactive relationship that exists between these three types of lexical information. While previous research has shown that memory networks are divided into separate systems which handle storage and processing for meaning and association (see Ferrand & New, 2004 for a review), the presence of these interactions suggests that connections exist between these individual memory networks, linking them to one another. As such, we suggest that these memory systems may be connected in such a way to form a three-tiered, interconnected system. First, information enters the semantic memory network, which processes features of concepts and provides a means of categorizing items based on the similarity of their features. Next, the associative network adds information for items based on contexts generated by reading or speech. Finally, the thematic network pulls in information from both the semantic and associative networks to create a mental representation of both the item and its place in

the world relative to other concepts. This study did not explore the timing of information input from each of these systems, but it may be similar to a dual-route model of reading and naming, in that each runs in parallel contributing the judgment and recall process (Coltheart, Curtis, Atkins, & Haller, 1993).

Viewing this model purely through the lens of semantic memory, it draws comparison to dynamic attractor models (Hopfield, 1982; Jones et al., 2015; McLeod et al., 2000). One of the defining features of dynamic attractor models is that they allow for some type of bidirectionally or feedback between connections in the network. In the study of semantic memory, these models are useful for taking into account multiple restraints such as links between semantics and the orthography of the concept in question. Our hypothesis extends this notion as a means of framing how these three memory systems are connected. The underlying meaning of a concept is linked with both information pertaining to its co-occurrences in everyday language and information relating to the general contexts in which it typically appears.

How then does this hypothesis lend itself towards the broader context of psycholinguistic research? One application of this hypothesis may be models of word recognition. One popular class of models are those based upon Seidenberg and McClelland (1989) "triangle model" (see Harley, 2008 for a review). They key feature of these models is that they recognize speech and reading based upon the orthography, phonology, and meaning of words in a bidirectional manner, similar to the models described above. Harm and Seidenberg (2004) developed a version which included a focus on semantics, with word meaning being related to input from the orthography and phonology components of the model. Our findings from the present study further suggest that thematic and associative knowledge is incorporated with meaning. One way of framing our results within this literature is to consider the semantic section of the triangle model as being comprised of these three tiers, and that concept information is processed to some degree on each of these domains. One area for future studies of this nature may be investigating how aspects of

orthography and phonology impact these memory networks. Additionally, future studies may wish to consider elements of thematic and associative knowledge when examining semantic based tasks, such as word recognition and reading, as thematic and associative information is interconnected with the semantic network. Ultimately, further studies will be needed to fully understand the interconnections between the semantic, thematic, and associative networks.

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Table 1

Summary Statistics for Stimuli

Variable	COS Low			COS Average			COS High		
	N	*M*	*SD*	*N*	*M*	*SD*	*N*	*M*	*SD*
COS	21	.115	.122	21	.461	.098	21	.754	.059
FSG Low	18	.062	.059	18	.122	.079	17	.065	.067
FSG Average	3	.413	.093	2	.411	.046	2	.505	.175
FSG High	NA	NA	NA	1	.697	NA	2	.744	.002
LSA Low	16	.174	.090	8	.220	.074	7	.282	.064
LSA Average	5	.487	.126	10	.450	.111	12	.478	.095
LSA High	NA	NA	NA	3	.707	.023	2	.830	.102

Note. COS: Cosine, FSG: Forward Strength, LSA: Latent Semantic Analysis.

Table 2

Summary Statistics for Hypothesis 1 t-Tests

Variable	M	SD	t	df	p	d	95%CI
Associative Intercept	.511	.245	20.864	99	< .001	2.086	1.734 - 2.435
Associative COS	-.030	.284	-1.071	99	.287	-0.107	-0.303 - 0.090
Associative FSG	.491	.379	12.946	99	< .001	1.295	1.027 - 1.559
Associative LSA	.035	.317	1.109	99	.270	0.111	-0.086 - 0.307
Semantic Intercept	.587	.188	31.530	101	< .001	3.122	2.649 - 3.592
Semantic COS	.059	.243	2.459	101	.016	0.244	0.046 - 0.440
Semantic FSG	.118	.382	3.128	101	.002	0.310	0.110 - 0.508
Semantic LSA	.085	.304	2.816	101	.006	0.279	0.080 - 0.476
Thematic Intercept	.656	.186	35.475	100	< .001	3.530	3.002 - 4.048
Thematic COS	-.081	.239	-3.405	100	< .001	-0.339	-0.539 - -0.137
Thematic FSG	.192	.306	6.290	100	< .001	0.626	0.411 - 0.838
Thematic LSA	.188	.265	7.111	100	< .001	0.708	0.488 - 0.924

Note. Confidence interval for d was calculated using the non-central t-distribution.

Table 3

MLM Statistics for Hypothesis 2

| Variable	beta	SE	t	p
Intercept	0.603	0.014	43.287	< .001
Semantic Judgments	0.079	0.008	9.968	< .001
Thematic Judgments	0.127	0.008	16.184	< .001
ZCOS	-0.103	0.017	-6.081	< .001
ZLSA	0.090	0.022	4.196	< .001
ZFSG	0.271	0.029	9.420	< .001
ZCOS:ZLSA	-0.141	0.085	-1.650	.099
ZCOS:ZFSG	-0.374	0.111	-3.364	< .001
ZLSA:ZFSG	-0.569	0.131	-4.336	< .001
ZCOS:ZLSA:ZFSG	3.324	0.490	6.791	< .001
Low COS ZLSA	0.129	0.033	3.934	< .001
Low COS ZFSG	0.375	0.049	7.679	< .001
Low COS ZLSA:ZFSG	-1.492	0.226	-6.611	< .001
High COS ZLSA	0.051	0.031	1.647	.100
High COS ZFSG	0.167	0.034	4.878	< .001
High COS ZLSA:ZFSG	0.355	0.143	2.484	.013
Low COS Low LSA ZFSG	0.663	0.078	8.476	< .001
Low COS High LSA ZFSG	0.087	0.049	1.754	.079
Avg COS Low LSA ZFSG	0.381	0.047	8.099	< .001
Avg COS High LSA ZFSG	0.161	0.027	5.984	< .001
High COS Low LSA ZFSG	0.099	0.058	1.707	.088
High COS High LSA ZFSG	0.236	0.023	10.263	< .001

Note. Database norms were mean centered. The table shows
main effects and interactions for database norms at low, average,
and high levels of COS and LSA when predicting participant
judgments.

Table 4

MLM Statistics for Hypothesis 3

Variable	beta	SE	z	p
Intercept	0.301	0.138	2.188	.029
Semantic Judgments	0.201	0.074	2.702	.007
Thematic Judgments	-0.001	0.075	-0.020	.984
Judged Values	0.686	0.115	5.956	< .001
ZCOS	0.594	0.179	3.320	< .001
ZLSA	-0.350	0.204	-1.714	.087
ZFSG	3.085	0.302	10.205	< .001
ZCOS:ZLSA	2.098	0.837	2.506	.012
ZCOS:ZFSG	1.742	1.306	1.334	.182
ZLSA:ZFSG	-1.017	1.484	-0.685	.493
ZCOS:ZLSA:ZFSG	24.572	6.048	4.063	< .001
Low COS ZLSA	-0.933	0.301	-3.099	.002
Low COS ZFSG	2.601	0.471	5.521	< .001
Low COS ZLSA:ZFSG	-7.845	2.204	-3.560	< .001
High COS ZLSA	0.233	0.317	0.737	.461
High COS ZFSG	3.569	0.470	7.586	< .001
High COS ZLSA:ZFSG	5.811	2.231	2.605	.009
Low COS Low LSA ZFSG	4.116	0.741	5.558	< .001
Low COS High LSA ZFSG	1.086	0.501	2.166	.030
High COS Low LSA ZFSG	2.447	0.811	3.018	.003
High COS High LSA ZFSG	4.692	0.388	12.083	< .001

Note. Database norms were mean centered. The table shows
main effects and interactions for database norms at low, average,
and high levels of COS and LSA when predicting recall.

Table 5

MLM Statistics for Hypothesis 4

Variable	b	SE	z	p
(Intercept)	-0.432	0.439	-0.983	.326
ACOS	0.314	0.550	0.572	.568
ALSA	0.501	0.463	1.081	.279
AFSG	0.898	0.337	2.667	.008
AIntercept	1.514	0.604	2.507	.012
(Intercept)	-0.827	0.463	-1.787	.074
SCOS	2.039	0.518	3.939	< .001
SLSA	1.061	0.455	2.335	.020
SFSG	0.381	0.289	1.319	.187
SIntercept	2.292	0.681	3.363	< .001
(Intercept)	0.060	0.599	0.101	.920
TCOS	0.792	0.566	1.401	.161
TLSA	0.896	0.529	1.694	.090
TFSG	-0.394	0.441	-0.894	.371
TIntercept	1.028	0.756	1.360	.174

Note. Each judgment-database bias and
sensitivity predicting recall for corresponding
judgment block. A: Associative, S: Semantic,
T: Thematic.
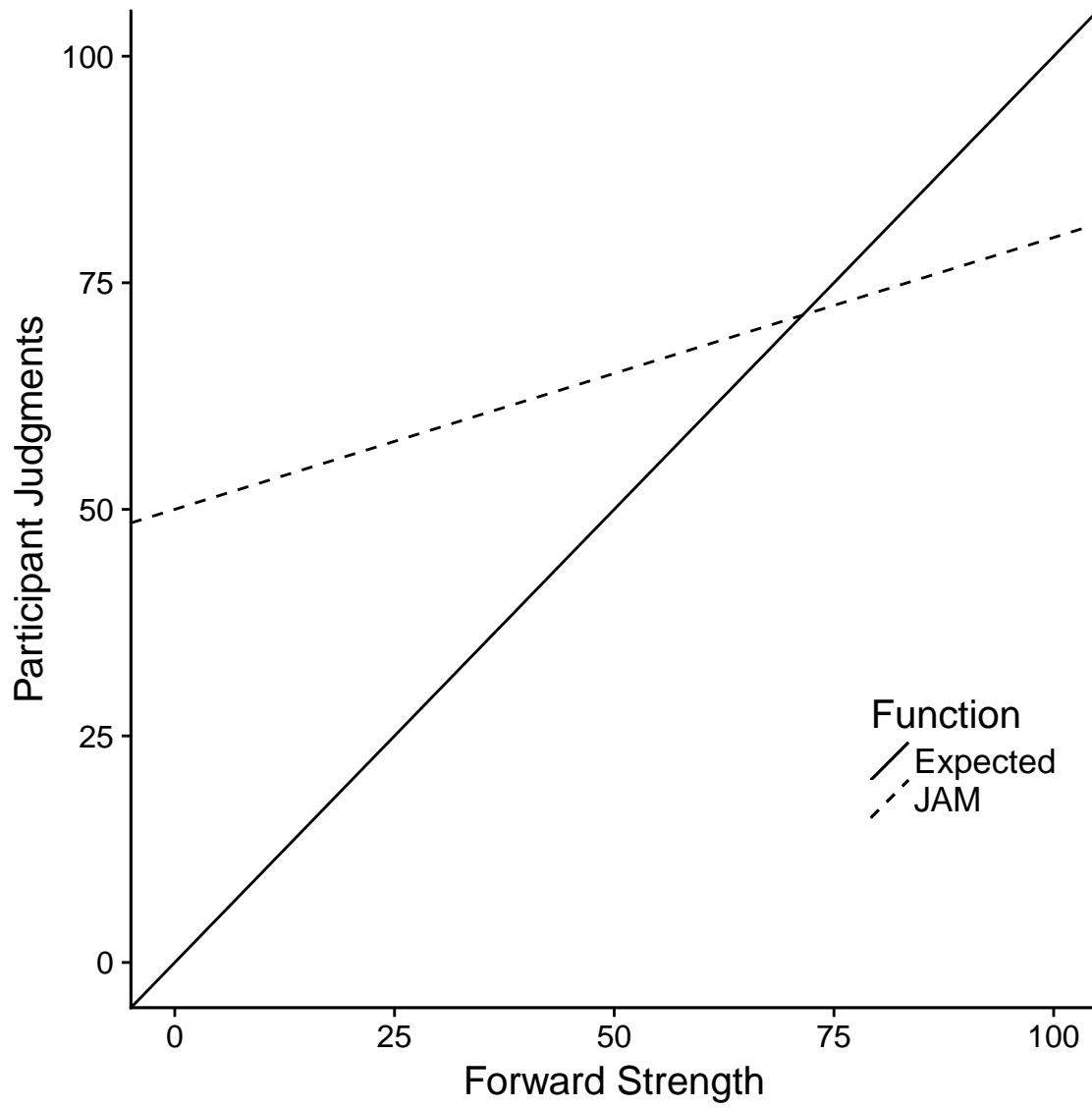
Figure 1. JAM slope findings from Maki (2007a). JAM is characterized by a high intercept (between 40 and 60) and a shallow slope (between 0.20 and 0.40). The solid line shows expected results if judgment ratings are perfectly calibrated with association norms.
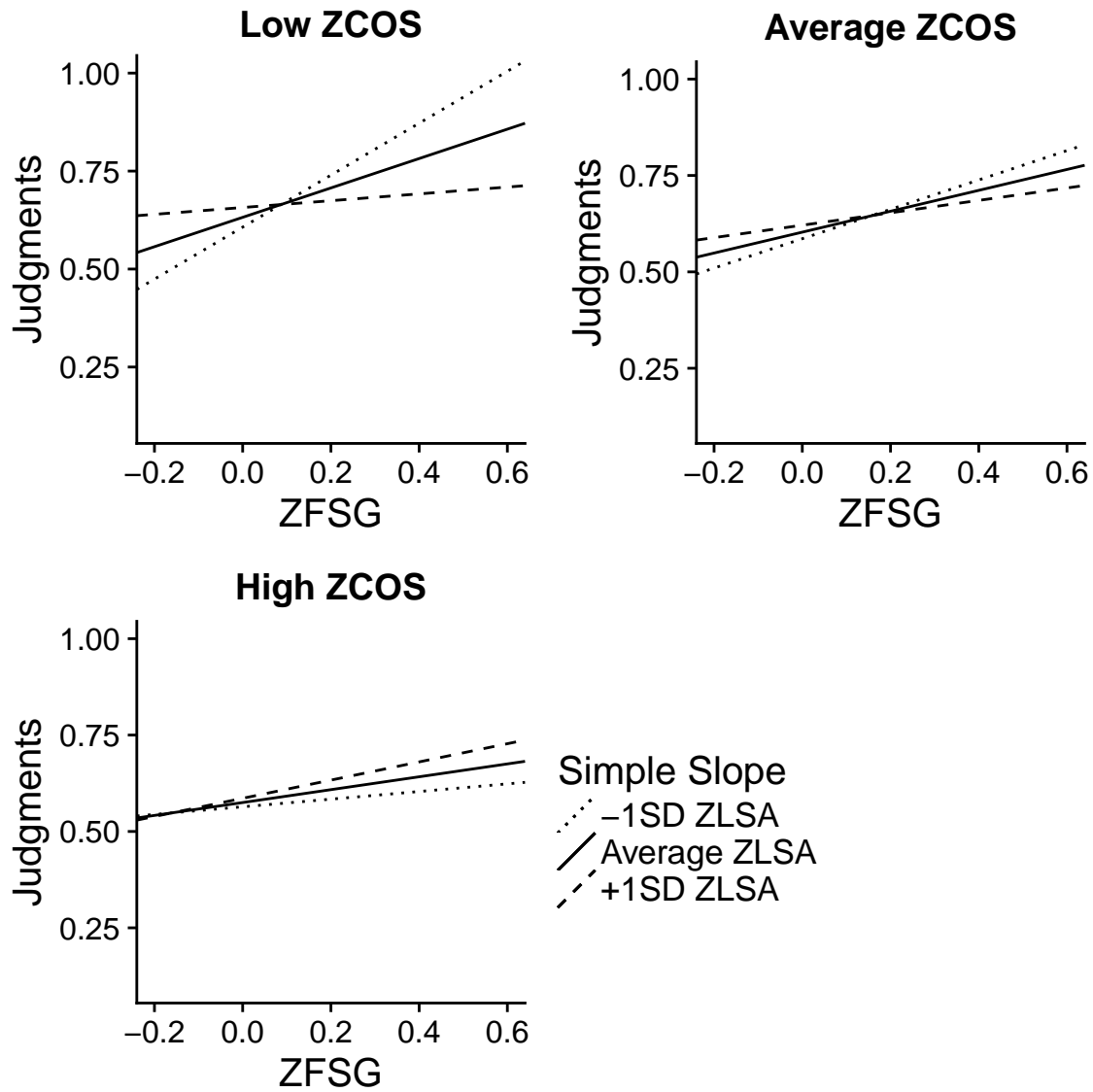
Figure 2. Simple slopes graph displaying the slope of FSG when predicting JORs at low, average, and high LSA split by low, average, and high COS. All variables were mean centered.
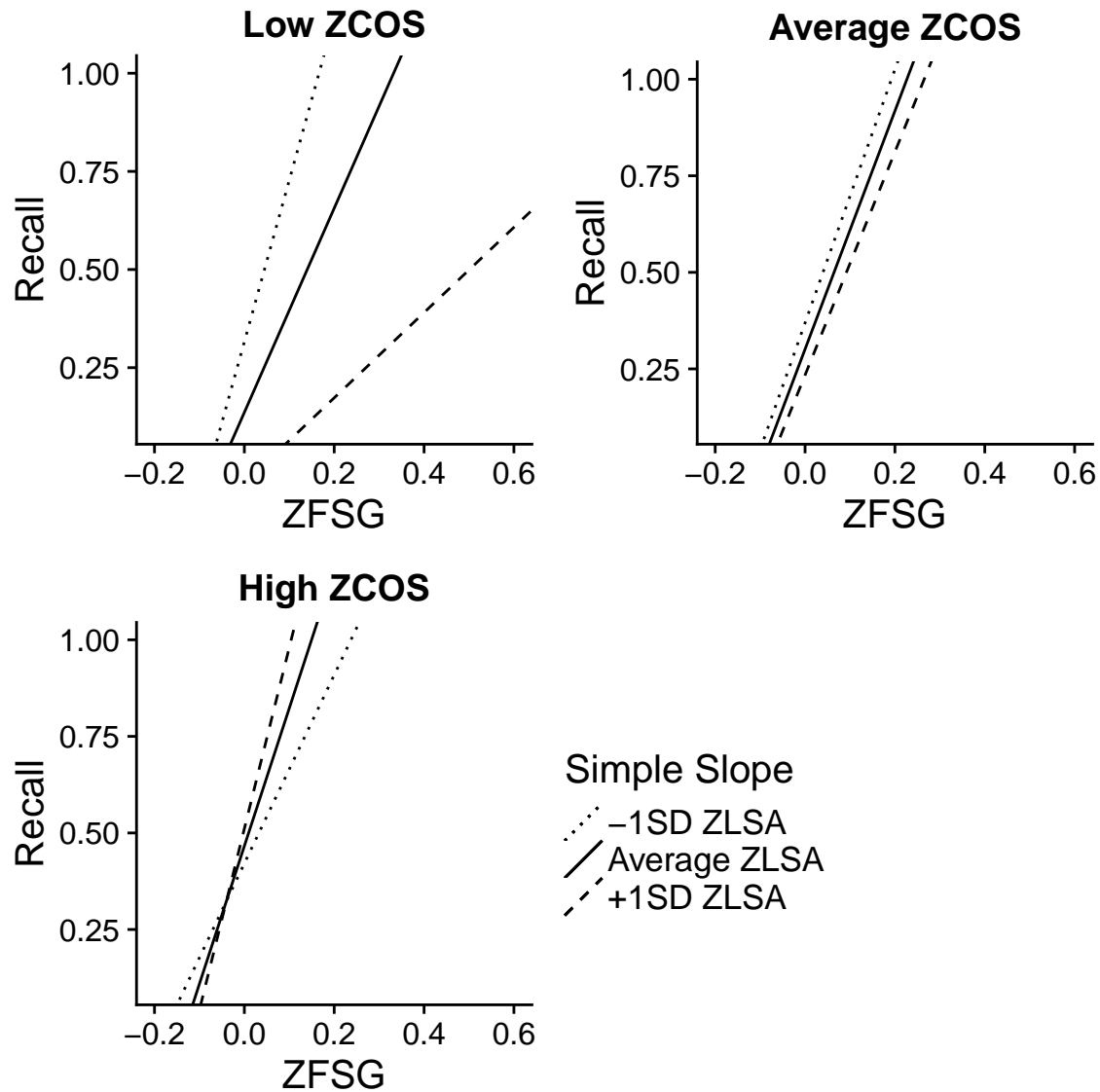
Figure 3. Simple slopes graph displaying the slope of FSG when predicting recall at low, average, and high LSA split by low, average, and high COS. All variables were mean centered.