Journal of the Association for Information Systems

Research Perspective ISSN: 1536-9323

# Controlling for Lexical Closeness in Survey Research: A Demonstration on the Technology Acceptance Model

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**Abstract:**

Word co-occurrences in text carry lexical information that can be harvested by data-mining tools such as latent semantic analysis (LSA). In this research perspective paper, we demonstrate the potency of using such embedded information by demonstrating that the technology acceptance model (TAM) can be reconstructed significantly by analyzing unrelated newspaper articles. We suggest that part of the reason for the phenomenal statistical validity of TAM across contexts may be related to the lexical closeness among the keywords in its measurement items. We do so not to critique TAM but to praise the quality of its methodology. Next, putting that LSA reconstruction of TAM into perspective, we show that empirical data can provide a significantly better fitting model than LSA data can. Combined, the results raise the possibility that a significant portion of variance in survey based research results from word co-occurrences in the language itself regardless of the theory or context of the study. Addressing this possibility, we suggest a method to statistically control for lexical closeness.

**Keywords:** TAM, Latent Semantic Analysis (LSA), Lexical Closeness, CBSEM, Measurement Theory.

Allen Lee was the accepting senior editor. This paper was submitted on February 18, 2016, and went through 3 revisions.

# 1 Introduction

In this research perspective paper, we present a new lexical aspect of the technology acceptance model (TAM) (Davis, 1989) and argue that there is more to TAM than just its current theory base: empirical research supports the theory extensively across IT contexts also because it represents connections among words as they are used in English. While we recognize that questionnaires not only measure the theory they pertain to but also may be influenced by a host of prejudices and priming related to the subjects, the researchers, and unrelated covariances introduced by the data-collection methods (see extensive discussion in Shadish, Cook, and Campbell (2002)), we present another, unrelated type of significant wording influence on the results. This significant influence pertains to the lexical closeness information embedded in language itself and that can be derived by analyzing word co-occurrences. Lexical closeness is the degree to which two terms or combinations of terms (including questionnaire measurement items and sentences) relate to each other as revealed through term co-occurrence in societal usage of the language[1]. This lexical closeness can be extracted through tools such as latent semantic analysis (LSA). LSA treats lexical closeness across documents as revealing shared inferences among the authors of those documents about the meaning of words (Landauer, Foltz, & Laham, 1998; Wild, Haley, & Bülow, 2011)[2].

In this paper, we demonstrate the power of such lexical closeness by replicating TAM results based solely on the lexical closeness of the keywords in the TAM measurement items as derived through LSA. In Section 2, we present LSA in more detail. In Section 3, we discuss the lexical closeness information that we derived from two newspaper corpora discussed.

In Section 4, we show that the phenomenal success of TAM may plausibly in part result from the lexical closeness of its measurement items. We do not do so to challenge TAM; rather, we do so to show that there is more to TAM than currently considered. TAM is by far the most cited theory in the management information systems (MIS) discipline. The analyses show that simply analyzing the co-occurrence of the keywords in its questionnaire as they appear in magazine and newspaper articles statistically supports both its measurement model (how questionnaire items load into constructs) and even partly the correlations among its constructs are supported statistically. Each corpus produced adequate factorial validity in a principal components analysis (PCA) and supported TAM through linear regressions on those PCA factors—as done in the original TAM study.

In Section 5, qualifying the conclusion that only relying on how its questionnaire keywords relate to each other in newspaper articles can support TAM, we show that, nonetheless, empirical questionnaire data can provide a significantly better model. To do so, we again replicate the analysis method in the original TAM but also add covariance-based structural equation modeling (CBSEM) analysis. The above analyses support previous findings that LSA can in some cases be applied to sort questionnaire items into groups by analyzing the lexical relationships among questionnaire items (Larsen & Bong, 2016). Arnulf, Larsen, Martinsen, and Bong (2014) have shown as much for several influential theories on leadership, which Nimon, Shuck, and Zigarmi (2015) have independently replicated. We extend those previous findings by showing that the constructs derived from those items at least partly correlate with each other as theory predicts. In Section 6, we reassuringly show how an existing CBSEM method can be applied to statistically control for lexical closeness covariance when examining empirical data. That analysis shows that TAM is not based solely on lexical closeness.

Taking a broader methodological perspective, that lexical closeness revealed by analyzing corpora that does not deal with TAM studies can produce specific expected theory-based patterns is a departure from classical measurement theory[3]. Thus, in Section 7, we discuss what implications this result has and the

[1] One can identify that societal use by creating a semantic space out of a large set (e.g., 500) of orthogonal topic dimensions derived through a decomposition of term co-occurrence patterns weighted by the uniqueness of those terms across a large corpus of documents. The lexical closeness of sentences (such as questionnaire items) is calculated through item vectors (combinations of terms). LSA provides many measures of the degree that terms or sentences appear or do not appear together. We chose correlation because that is the type of data that Gefen et al. (2003), whose study we replicate, used. Currently, CBSEM can also support ordered measures, such as cosine distances, and not only rational numbers. We duly replicated the analyses with cosine distances, too, which resulted in equivalent results. Appendix E details how we created these measures.

[2] In this paper, we use the term lexical closeness to avoid misunderstandings. Lexical means pertaining to the meaning of words without reference to grammar and sentence construction. Semantic, by some definitions, is about word meaning based also on grammar. LSA does not consider grammar and sentence construction.

[3] To clarify, this study is not about how the choice of words or language can bias how subjects respond to questionnaire items as researchers have previously documented (Cook & Campbell, 1979, Shadish et al., 2002). It is about showing that preexisting

intriguing idea that, to some extent, we can predict the results of empirical survey research that uses questionnaires by analyzing lexical closeness even without collecting data from subjects. We suggest that a possible reason for this ability to partly predict the results of survey research may be that, for language to work as a medium of communication, people have to somewhat think alike. This thinking alike should apply both to people who write the documents that LSA analyzes and to subjects who complete questionnaires. This may be inevitable, but it comes at a cost: some of the covariance in survey research may relate to lexical instrumentation and have nothing to do with the subjects except that the measurement items the subjects respond to and the articles the lexical closeness measures are based on are all in English. In this paper, we demonstrate that lexical closeness should and can be accounted for. We also show that lexical closeness does not replace the need for empirical data.

## 2 Deriving Lexical Closeness through LSA

We can learn much from word co-occurrences. Importantly, when researchers analyze word co-occurrences with LSA, they can adopt a data-driven and relatively objective approach and, thus, produce “meaning” devoid of researcher presuppositions (Evangelopoulos, Zhang, & Prybutok, 2012). LSA is a statistical modeling tool that analyzes term co-occurrences in preexisting corpora. LSA creates a “semantic space” (though perhaps “lexical space” is more technically correct because the tool ignores grammar and tense) by analyzing the co-occurrence of chosen keywords and phrases across documents in large corpora (Landauer et al., 1998). In producing the sematic space, LSA considers not only word co-occurrences per se but also words that may be related to each other because they co-occur often with the same set of other words[4]. A researcher can then analyze other documents against this semantic space. Landauer (2007, p. 31) claims that LSA “demonstrates a computational method by which a major component of language learning and use can be achieved”. Less presumptuously, researchers continue to debate why LSA actually does what it does and what mental process it might be simulating (Evangelopoulos et al., 2012; Valle-Lisboa & Mizraji, 2007).

Underlying LSA is the realization that to cognitively understand what a term (i.e., a word or a combination of words) means requires considering its use in other documents (Wild et al., 2011). LSA dynamically creates this “semantic” space. LSA starts by creating a term-document co-occurrence matrix (known as the TDM matrix) across many documents in diverse corpora. Often, words that contribute little lexical information, such as “if” and “the”, are removed prior to the creation of the TDM (such words are known as “stop words” in LSA parlance). There are standard listings of stop words in English. Typically, the retained words are also stemmed using Porter’s (1980) algorithm or an equivalent one prior to the creation of the TDM matrix. This stemming creates one entry in the matrix for the same word regardless of its tense or whether it is singular or plural and so on. The algorithm then calculates the entropy of the terms across the documents and applies singular value decomposition (SVD) on the entropy data to produce vectors/factors that relate the terms to the documents they came from. SVD performs a transformation that is akin to dimension reduction (Wall, Rechsteiner, & Rocha, 2003). SVD accordingly enables researchers to identify connections among terms, such as underlying common factors, through a linear decomposition of an existing matrix into its principal components (Landauer & Dumais, 1997). This linear decomposition accounts for how often terms appear together or appear together through their relationships to other terms (Landauer et al., 1998). LSA typically approximates this linear decomposition through a 300 or higher dimensional semantic space that represents each term as a vector. Then, by applying either a cluster analysis or a PCA on the SVD results of that matrix, a researcher can show documents that share terms of interest to cluster together in a cluster analysis or to load together in a PCA based on assessing their co-occurrence (Deerwester, Dumais, Furnas, Landauer, & Harshman, 1990; Valle-Lisboa & Mizraji, 2007). In this manner, LSA allows a researcher to discover the revealed closeness of terms to other terms and documents to other documents in corpora (Evangelopoulos et al., 2012)[5].

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patterns of words co-occurring in regular language usage are a source of variance that, as of itself, may in some cases be enough to significantly produce the expected model.

[4] As an example, the words “USA” and “United States of America” will be closely related in such an analysis because, even if individual writers might often choose exclusively one term over the other to suit their magazines, both terms will appear in high co-occurrence with other words such as “Republicans” “Democrats” “map” “flag” and “population” and in contexts of other countries such as Cuba, Russia, Canada, and Mexico.

[5] For more discussion on LSA, refer to Deerwester et al. (1990) and Valle-Lisboa and Mizraji (2007). On analyzing co-occurrence correlations and, hence, why keywords may be related even if they do not appear together in the same document, see Kontostathis

Terms that have closely related meaning tend to appear with high degrees of closeness in LSA analyses across many randomly selected documents (Gomez, Boiy, & Moens, 2012).

Landauer et al. (1998) argue that the LSA algorithm is analogous to some aspects of human information retrieval and semantic memory. They claim that LSA simulates human thought so well that it can answer multiple choice questions in introduction to psychology exams almost as well as students can (Landauer et al., 1998) and that it scores on TOFEL exams as high as nonnative speakers do (Landauer & Dumais, 1997). Landauer and Dumais (1997) have even argued that LSA may be simulating some of the processes by which people infer knowledge beyond information that is available to them. Extensive research on LSA shows that semantic closeness measures how words aggregate into groups through shared meanings that make sense to an objective person (Landauer et al., 1998). Indeed, LSA does identify synonyms (Valle-Lisboa & Mizraji, 2007). Moreover, the lexical closeness that LSA produces is sufficient to determine how close the synonym is to the original word based on the frequency in which they tend to appear together (Islam, Milios, & Keselj, 2012). Accordingly, researchers have presented LSA as a model that, to some extent, is a contextualization of a "generative lexicon" model of knowledge (Kintsch et al., 2007, p. 472) where knowledge can be partially derived through the written experience of others. Researchers have also convincingly shown LSA to classify MIS papers into their core research topics by analyzing the semantic closeness of the keywords in their abstracts (Evangelopoulos et al., 2012; Sidorova, Evangelopoulos, Valacich, & Ramakrishnan, 2008). LSA can also successfully classify emails into spam versus non-spam (Gomez et al., 2012). Having said all that, it should nonetheless be clear that LSA does not provide a perfect representation of human knowledge, nor does it account for all the information in the text such as morphology, syntax, and word order. It does, however, provide an estimate of at least how people group words and, thus, provides a basis for determining their lexical closeness (Kintsch, McNamara, Dennis, & Landauer, 2007). Importantly, LSA is not based on researchers' preexisting knowledge, and so they can apply it as an automated tool to any written text (Kintsch et al., 2007) with reasonable expectations for objectivity.

Once LSA has created a semantic space, a researcher can use the tool to analyze the semantic space in further ways, such as how other texts that are not part of the corpora are close to each other based on that semantic space. In the case of this paper, we conducted such an analysis; specifically, we assessed TAM questionnaire items based on unrelated semantic spaces created out of newspaper corpora. To do so, we used LSA to create two independent semantic spaces out of two unrelated large newspaper corpora. We then used LSA to stem the TAM questionnaire terms and project them onto each of those semantic spaces. We created the projection of each questionnaire measurement item as the sum of the vectors of its terms independently for each semantic space so that we ran two parallel analyses. Having two parallel unrelated analyses produce equivalent results arguably adds to the reliability of the claims being made. Per each sematic space, the projection of the TAM items yielded *n* vectors where *n* is the number of items. We used the standard cosine formula (Dumais, 1991; Nakov, Popova, & Mateev, 2001) to evaluate the closeness of each pair of questionnaire items. We also ran a Pearson correlation. Pearson correlations are an alternative similarity measure (Landauer et al., 1998; Rohde, Gonnerman, & Plaut, 2006) and allow analyses in CBSEM.

# 3 Corpora Used in This Demonstration

The accuracy of lexical closeness analysis depends on having an appropriate and large context corpus. For this paper, we used two such large corpora, which both focused on descriptions of human decision making, that we repurposed from another project (Hayward, Fitza, & Larsen, 2008; Fitza, Larsen, & Hayward, 2007)[6]. These authors selected articles for the corpora because they contained reference to one or more Fortune 500 CEOs in their year of publication. One corpus sampled business press reports and the other news reports:

1. The business corpus contained excerpts from *The Wall Street Journal*, *Business Week*, *Forbes*, and *Fortune*. It had 84,836 articles from 1998-2007 that contained 45,816,686 total words and 169,235 unique words that we analyzed as 132,267 stems.

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and Pottenger (2006). On its use in the IS discipline, see Evangelopoulos et al. (2012), Sidorova et al. (2008), and Larsen, Monarchi, Hovorka, and Bailey (2008a).

[6] We removed these citations during review.

2. The news corpus contained excerpts from *The New York Times*, *Los Angeles Times*, *Chicago Tribune*, *The Washington Post*, *The Boston Globe*, *USA Today*, *Houston Chronicle*, *San Francisco Chronicle*, and *The Denver Post*. It had 162,929 articles from 1998-2007 that contained 107,239,064 total words and 286,312 unique words that we analyzed as 231,606 stems.

TAM should conceivably be more related to business reports than to news reports because ICT adoption is often related to, and has been studied about, ICT adoption in business and organizational contexts. Nonetheless, stories about ICT do appear also in news reports. Each corpus had one column for each measurement item and one row for each SVD dimension (500 rows in total). Appendix E presents the process by which we applied LSA to these corpora.

# 4 Replicating the Original TAM Study on Lexical Closeness Data

In this section, we discuss how we replicated TAM on lexical closeness data for each of the two corpora. Figure 1 summarizes the logic for why such data might conceivably relate to TAM. Preexisting usage patterns in English, such as synonyms, presumably create a disposition among people who write newspaper articles to associate those words in their writing (arrow 1) and prejudice and priming based on that predisposition among subjects who complete questionnaires (arrow 2). As a result, the cognitions of both groups should somewhat overlap (arrow 3). LSA implies arrow 1, and Cook and Campbell (1979) imply arrow 2. Arrow 3 is a transitive logic derivation of those implications. Allowing that LSA can identify aspects of lexical closeness (arrow 4) and that choice of wording can prejudice and prime subjects answering questionnaires (Cook & Campbell, 1979)[7], which leads to arrow 5, one might expect (arrow 6) some degree of shared variance between the lexical closeness that LSA identifies in news and business reports and empirical data collected from subjects. That source of shared variance is the lexical information embedded in the daily usage of the language.

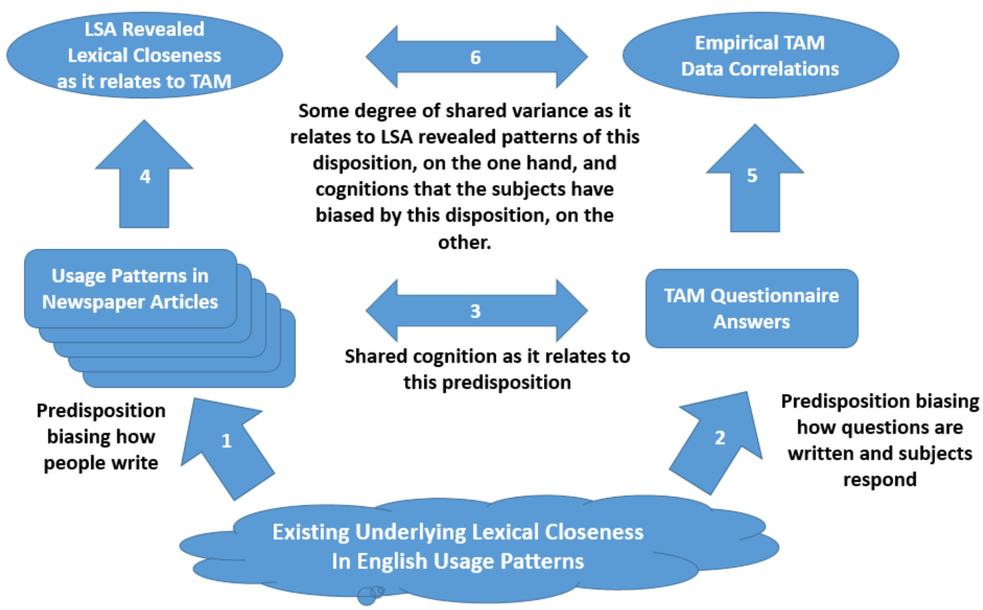



**Figure 1. Summary of Why LSA Should Apply to TAM**

In other words, we cannot rule out that language usage patterns in one context, such as revealed by analyzing text corpora, might at least in part produce the expected answers in another context, such as in answering a questionnaire about ICT acceptance. We do not assert that LSA predicts how people will complete questionnaires. Rather, we assert that common, preexisting lexical patterns affect how people write texts (and,

[7] To avoid misunderstandings, by prejudicing and priming, we mean that a choice of words that subconsciously reminds the subject of something can affect an answer the subject gives to a survey question (Cassino & Erisen, 2010). An example of such priming is that the choice of words in a previous question can change how a subject answers a subsequent question (McFarland, 1981), framing the context.

hence, LSA results) and how people design and answer questionnaires (and, hence, the people who answer TAM questionnaires). As such, because both draw on shared preexisting lexical patterns, the results of text analysis in LSA and related empirical questionnaire answers should overlap to some degree[8].

## 4.1 Reasons for Expecting a Replication of TAM in Particular

These shared preexisting lexical patterns might be especially pertinent in the case of TAM[9]. Davis (1989, pp. 323-326) pretested TAM's questionnaire items extensively to show that people understand and group the keywords in the TAM items as the model expects. Davis performed this step before pilot testing the model with questionnaire data. Therefore, if LSA synthesizes lexical patterns as Landauer and Dumais (1997) claim, then the lexical patterns that LSA identifies as an integral part of the language should presumably also somewhat determine how people answer TAM questionnaires. Notice that the pretest David conducted also sought lexical grouping except that Davis did so by explicitly asking people to Q sort index cards while LSA does so implicitly through analyzing word co-occurrences. The notion that wording can prejudice, influence, and prime how people respond to questionnaires is not new (Cook & Campbell, 1979, Shadish et al., 2002) and should apply even more so in the case of TAM because its questionnaire items are reflective. Reflective items are measurement items that reflect a latent construct and are reasonably interchangeable with each other because they overlap considerably in their meaning (Jarvis et al., 2003). As reflective items, all the PU items were explicitly designed to share meaning with each other, as were the PEOU and the intended use items. That shared meaning was reflected explicitly in the Q sort that verified the TAM items before their pretest. Presumably, equivalent groupings should apply also to daily language usage. And so, just as empirical data load on a TAM questionnaire with a nice PCA pattern, so too should the LSA-derived lexical closeness data of the same items[10]. Accordingly, allowing that LSA identifies indirectly how people naturally group words to reveal related meanings and that this grouping rather accurately corresponds to actual word groupings in language (Landauer & Dumais, 1997) and allowing that, in the very creation of TAM, Davis applied a deliberate process to identify how people sort the TAM items into groups, we have no reason to expect an overlap between how people apparently group the TAM keywords in newspaper articles and how the original group who pretested TAM grouped them.

## 4.2 Statistically Replicating the Original TAM Study 2 in Davis (1989) with LSA Data

In this section, we show that the lexical information embedded in the English language, as derived from either of the newspaper corpora, provides sufficient lexical closeness among the original TAM questionnaire items to actually replicate the model[11]. We tested this replication in two stages. In the first stage, we derived the lexical closeness of the original TAM scales based on the semantic spaces of each of the two corpora. We took the wording of the PU and PEOU items from Davis (1989). As Davis did not include the wording of the intended use items, we added those items based on the same studies as described in Davis (1985). We performed the lexical closeness analysis with LSA independently on each of the two corpora. After we extracted the LSA dimensions and correlations, the remainder of the analysis emulated the methodology that Davis (1989) applied: running a PCA and then regression models on the PCA supported factors. In Section 5, we discuss how we performed the analysis using CBSEM on the same data. We analyzed the lexical closeness data of each corpus separately. We purposely analyzed the data in the way TAM originally did to show that the replication with LSA lexical closeness measures is not an artifact of applying CBSEM.

The original TAM paper (Davis, 1989) reports on two studies. The first dealt with actual reported email and file editor use with 10 items each for perceived usefulness (PU) and perceived ease of use (PEOU) and

[8] Note that we do not claim that an exact pattern of correlations between items can be reconstructed. Rather, we claim only that such items do correlate regardless of the exact correlation coefficients between the many items.
[9] There are thousands of papers that have replicated the original TAM study, and many have proposed extensions to it. Therefore, we chose their originating source as a common denominator so that the conclusions could apply to as broad as possible a number of TAM studies and be of interest to as many researchers as possible. That common denominator is that all the TAM studies, as far as we could verify, rely on the core constructs of PU, PEOU, and behavioral intentions introduced in the original TAM study and almost universally apply the same keywords.
[10] Notice the contrast to classical measurement theory. In classical measurement theory (see Bollen (1989) for a detailed review of how classical measurement theory is applied in CBSEM), the model is assumed to be out there in the real world. The empirical data are assumed to reflect and support this model. The error variance is attributed to either how the subjects respond to the data collection instrument or to missing elements in the model. The correctness of the model in classical measurement theory has nothing to do with lexical patterns.
[11] Note that LSA does not require that the TAM items appear in their entirety in the documents used to create the semantic space. It is sufficient that sections of keywords inside each item appear. Appendix F shows a sample of such results.

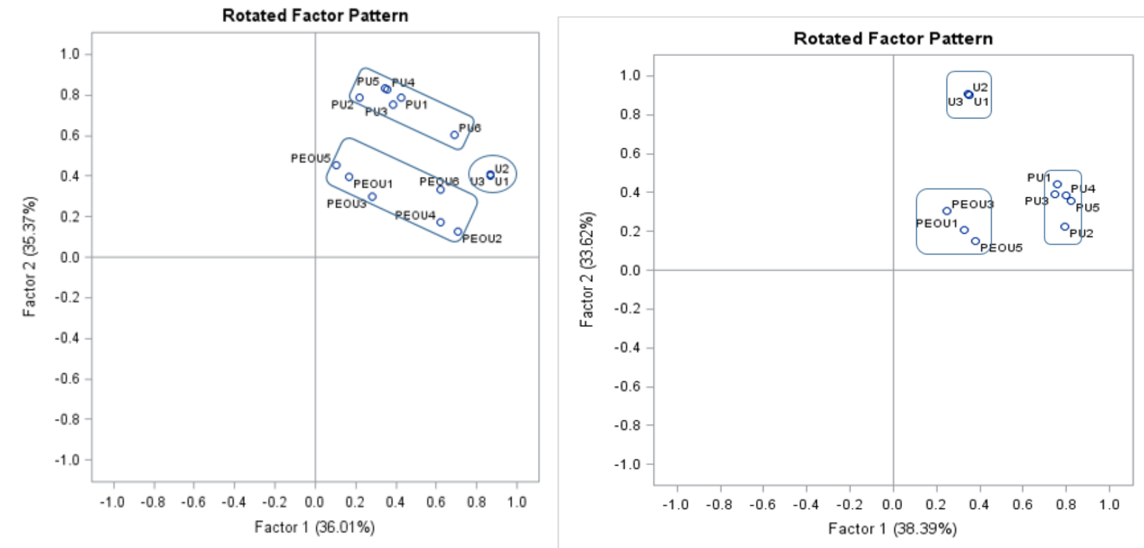
one item for self-reported use. Based on that study, Davis refined the items in the second study to six items each for PU and PEOU and three items for intended use. Because subsequent TAM studies built on the PU and PEOU scales of the refined second study, the replication analysis we performed dealt with the 15 items in that second study (which we call "study 2"). Appendix A shows the items.

To test the measurement model, we ran a PCA on the lexical closeness measures of the TAM scales, which conceptually replicates the PCA analysis that Davis (1989) ran on questionnaire data. Table 1 (left set of columns) shows the results of the PCA on the business corpus after a varimax rotation. The PCA produced three eigenvalues above 1 (10.7256, 1.2263, 1.1751); the fourth eigenvalue was 0.4003. The rotated PCA with all the 15 items shows a clear grouping of the intended use items (U1-U3), PEOU items, and PU items but with cross loadings of PU6 and PEOU 2, 4, and 6. We bold the high loadings to emphasize them. After removing those items with high cross loadings (see the right set of columns), the item loading pattern looked good. We show communality with the prefix "Com"). TAM studies commonly remove some of the PU and PEOU items. Had the data been data from survey research that applied questionnaires, the criteria for a good item loading pattern in a PCA would have been above .60 on the related factor and below .40 on the other factors and communality above .707 (Hair, Black, Babin, & Anderson, 2005). Applying that rule of thumb, the item loading pattern in Table 1's right column is good. Figure 2 shows the diagram of item loadings on the first two factors. The left diagram shows that pattern for all the items and the right one for only the retained items. Even in the left diagram (which retained all the items), one can see a discernable pattern of items' grouping by their prefixes even if this grouping was clearly not linear and as such not registered with a PCA. The diagrams add overlays to emphasize these item groupings. Cronbach alphas were .97 for intended use 1-3, .95 for PU 1-5, and .88 for PEOU 1, 3, and 5. These results support the measurement model with the business corpus. Note also that, despite the need to remove items in the original TAM scales, as shown in Table 1, we did not need to so in the CBSEM replication we conducted on Gefen, Karahanna, and Straub's (2003) data, which we discuss in Section 5.

**Table 1. Business Corpus Data**

| | Factor1 | Factor2 | Factor3 | Com | | Factor1 | Factor2 | Factor3 | Com |
|---|---|---|---|---|---|---|---|---|---|
| **U2** | **0.86907** | 0.40504 | 0.19680 | .958 | **PU5** | **0.82055** | 0.35466 | 0.36333 | .931 |
| **U1** | **0.86830** | 0.41011 | 0.20033 | .962 | **PU4** | **0.79816** | 0.38462 | 0.35881 | .914 |
| **U3** | **0.86697** | 0.40847 | 0.20254 | .960 | **PU2** | **0.79326** | 0.22699 | 0.31219 | .778 |
| **PEOU2** | **0.70404** | 0.12809 | **0.57546** | .843 | **PU1** | **0.75914** | 0.44000 | 0.40769 | .936 |
| **PU6** | **0.69003** | **0.60282** | 0.32128 | .923 | **PU3** | **0.74896** | 0.39306 | 0.26379 | .785 |
| **PU5** | 0.34586 | **0.83048** | 0.33954 | .925 | **U2** | 0.34383 | **0.90619** | 0.23541 | .995 |
| **PU4** | 0.35674 | **0.82846** | 0.32121 | .917 | **U3** | 0.34790 | **0.90374** | 0.24080 | .996 |
| **PU1** | 0.42266 | **0.78787** | 0.37465 | .940 | **U1** | 0.35103 | **0.90368** | 0.23717 | .996 |
| **PU2** | 0.21945 | **0.78606** | 0.30406 | .759 | **PEOU1** | 0.32833 | 0.20752 | **0.84608** | .867 |
| **PU3** | 0.38659 | **0.75265** | 0.24893 | .778 | **PEOU3** | 0.24950 | 0.30563 | **0.80963** | .811 |
| **PEOU1** | 0.16977 | 0.39661 | **0.80290** | .831 | **PEOU5** | 0.37911 | 0.14954 | **0.77593** | .768 |
| **PEOU3** | 0.28167 | 0.29929 | **0.79139** | .795 | | | | | |
| **PEOU5** | 0.10620 | 0.45632 | **0.72331** | .743 | | | | | |
| **PEOU4** | **0.61784** | 0.17211 | **0.70324** | .906 | | | | | |
| **PEOU6** | **0.61988** | 0.33600 | **0.64184** | .909 | | | | | |
| **Varimax-rotated factor loadings (all items included)** | | | | | **Varimax-rotated factor loadings (only retained items included)** | | | | |

| | PU | PEOU | USE | | PU | PEOU | USE |
|---|---|---|---|---|---|---|---|
| **PU** | 1 | | | **PU** | 1 | | |
| **PEOU** | 0.77039 | 1 | | **PEOU** | 0.72238 | 1 | |
| **USE** | 0.77333 | 0.72355 | 1 | **USE** | 0.72653 | 0.56059 | 1 |
| **Factor Pearson correlations** | | | | **Factor Pearson correlations** | | | |




**All Items Included** **Only Retained Items Included**

**Figure 2. Business Corpus Data Graphics**

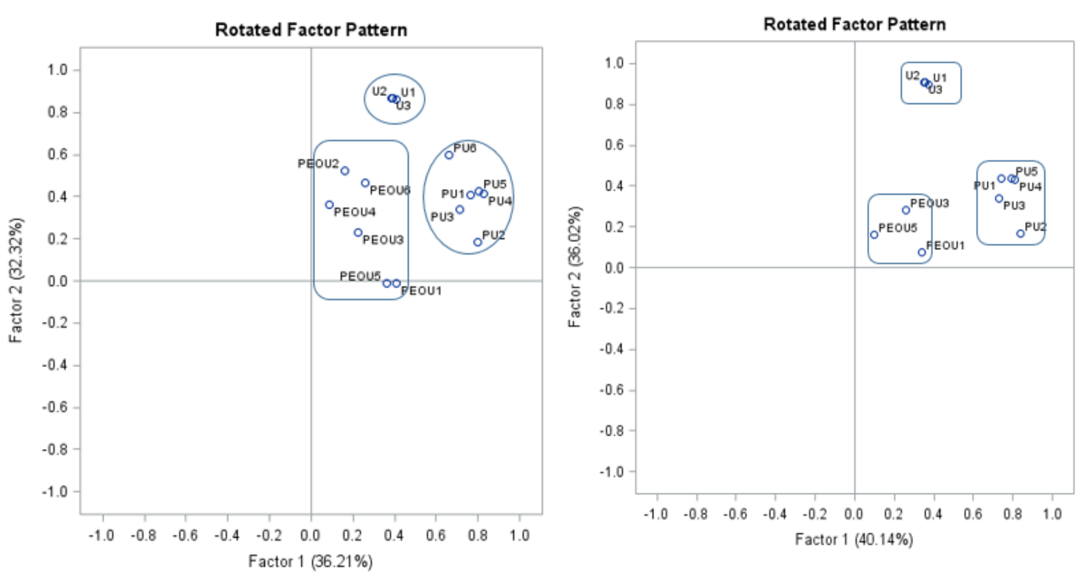
Running the same analysis on the news corpus (see Table 2) produced remarkably equivalent results even though the two corpora had no documents in common and came from an entirely different set of sources (albeit with potentially overlapping topics). The PCA produced three eigenvalues above 1 (9.2635, 1.5538, 1.0765); the fourth was 0.5006. As we can see in the left set of columns, the rotated PCA shows a clear grouping of the U, PEOU, and PU items but with cross loadings of the same PU6, PEOU2, PEOU6, and (slightly) PEOU4 items. After removing items with high cross loadings including PEOU4, shown in the right set of columns, the results show a nice item loading pattern. Again, even retaining all the items, we can see a discernable pattern of items' grouping together by their prefix in Figure 3. Cronbach alphas were .94 for intended use 1-3, .93 for PU 1-5, and .68 for PEOU 1, 3, and 5. These results support the measurement model also with the news corpus.

Next, we ran a structural model analysis on each corpus independently. As in the original TAM study 2 (Davis, 1989), we ran two linear regressions predicting intended use based on PU and PEOU and predicting PU based on PEOU. Doing the analysis this way conceptually parallels Davis' TAM study 2 except that we ran the analysis on lexical closeness data rather than on questionnaire data. We created the regression constructs by taking the algebraic average of the items assigned to each factor—the same method as Davis applied. The intended use, PU, and PEOU constructs were the averages of each of the factors on the right-hand side columns of Tables 1 and 2. We expected that one may plausibly expect that the regressions will be somewhat significant also with lexical closeness data because, just as each U, PU, and PEOU item may constitute a synonym with other items in the same construct, there might also be a weaker synonym with items in the other two constructs. For example, people may write about how to "accomplish tasks more quickly" (PU1) and about how it is "easy for me to become skillful" (PEOU5) in the same document even if less frequently than with "make it easier to do my job" (PU5). If so, then PU1 and PU5 would load on one PCA factor together with the other PU items but still be correlated with PEOU5. That correlation would be revealed in the linear regression.

**Table 2. News Corpus Data**

| | Factor1 | Factor2 | Factor3 | Com | | Factor1 | Factor2 | Factor3 | Com |
|---|---|---|---|---|---|---|---|---|---|
| **PU4** | **0.82660** | 0.41158 | 0.25115 | .916 | **PU2** | **0.83614** | 0.16864 | 0.19769 | .767 |
| **PU5** | **0.80257** | 0.42582 | 0.29898 | .915 | **PU4** | **0.80973** | 0.42983 | 0.26678 | .912 |
| **PU2** | **0.79703** | 0.18230 | 0.21660 | .715 | **PU5** | **0.79278** | 0.43938 | 0.29720 | .910 |
| **PU1** | **0.76670** | 0.40888 | 0.34246 | .872 | **PU1** | **0.74264** | 0.43647 | 0.35939 | .871 |
| **PU3** | **0.71487** | 0.34133 | 0.21075 | .672 | **PU3** | **0.73018** | 0.34001 | 0.19577 | .678 |
| **PU6** | **0.66238** | **0.59882** | 0.37052 | .934 | **U3** | 0.35177 | **0.90636** | 0.21232 | .990 |
| **U2** | 0.38835 | **0.86689** | 0.24117 | .960 | **U2** | 0.35457 | **0.90555** | 0.21159 | .991 |
| **U3** | 0.38783 | **0.86600** | 0.23813 | .957 | **U1** | 0.37203 | **0.89870** | 0.21384 | .992 |
| **U1** | 0.40530 | **0.86035** | 0.24133 | .963 | **PEOU1** | 0.33869 | 0.07575 | **0.79244** | .748 |
| **PEOU4** | 0.08881 | 0.36358 | **0.83052** | .830 | **PEOU5** | 0.09824 | 0.16274 | **0.75753** | .610 |
| **PEOU3** | 0.22330 | 0.23155 | **0.76614** | .690 | **PEOU3** | 0.25989 | 0.28177 | **0.68012** | .609 |
| **PEOU6** | 0.25987 | **0.46297** | **0.74546** | .838 | | | | | |
| **PEOU1** | 0.40885 | -0.01046 | **0.72944** | .699 | | | | | |
| **PEOU2** | 0.16353 | **0.52208** | **0.72819** | .830 | | | | | |
| **PEOU5** | 0.36071 | -0.01305 | **0.52022** | .401 | | | | | |
| **Varimax-rotated factor loadings (all items included)** | | | | | **Varimax-rotated factor loadings (only retained items included)** | | | | |

| | PU | PEOU | USE | | PU | PEOU | USE |
|---|---|---|---|---|---|---|---|
| **PU** | 1 | | | **PU** | 1 | | |
| **PEOU** | 0.66650 | 1 | | **PEOU** | 0.58965 | 1 | |
| **USE** | 0.75911 | 0.61760 | 1 | **USE** | 0.72432 | 0.49369 | 1 |
| **Factor Pearson correlations** | | | | **Factor Pearson correlations** | | | |




**All Items Included** **Only Retained Items Included**

**Figure 3. News Corpus Data Graphics**

Table 3 shows the results of those regressions. The intercepts were zero because LSA produces standardized measures. The business corpus analysis produced a significant model with intended use as the dependent variable ($F = 280.81$, $p < .0001$, $R^2 = .53$) and a significant model with PU as the dependent variable ($F = 543.47$, $p < .0001$, $R^2 = .52$). The news corpus analysis produced a significant model with intended use as the dependent variable ($F = 281.84$, $p < .0001$, $R^2 = .53$) and a significant model with PU as the dependent variable ($F = 265.44$, $p < .0001$, $R^2 = .35$). Thus, Table 3 supports the expected structural model patterns with both the business corpus and the news corpus. Note that the corpora do not overlap and that Hayward et al. (2008) and Fitza et al. (2007) drew the sample texts we took from each corpus from a very large sample[12].

**Table 3. Replicating TAM with Data Derived through LSA from News and Business Corpora**

| Business corpus | | | | News corpus | | | |
|---|---|---|---|---|---|---|---|
| **To-from** | **PEOU** | **PU** | **Intercept** | **To-from** | **PEOU** | **PU** | **Intercept** |
| **Intended use** | 0.12 | 0.81** | 0 | **Intended use** | 0.15** | 0.73** | 0 |
| **PU** | 0.97** | | 0 | **PU** | 0.81** | | 0 |
| ** significant at the 0.01 level | | | | | | | |

# 5 Comparing LSA Text Analysis Results with Questionnaire Data

As Section 4 shows, we derived LSA sematic closeness values for the original TAM items and ran PCA and linear regressions as done in the original TAM study with those values. The results demonstrate that lexical information embedded in the English language as derived by analyzing word co-occurrences in newspapers articles is sufficient to support TAM. Further, we obtained such results with two independent corpora, which increases the validity of that claim. In this section, we verify that CBSEM with its more demanding statistical validity tests can also support such replication and compare the results of analyzing lexical-derived data with empirical published questionnaire data. In Section 6, we build on these CBSEM results to suggest how an established method of comparing datasets in CBSEM may be a possible method to statistically control for the lexical information embedded in the language.

## 5.1 Replicating TAM with the Lexical Closeness of the Gefen et al. (2003) Items

Because Davis (1989) does not provide empirical data, we compared the survey data available in Gefen et al. (2003) with the lexical closeness measures of those same items. These items apply to online books and CD purchases. Appendix B shows the items that Gefen et al. used. Gefen et al. labeled what Davis in Appendix A called U as USE. Gefen et al. is among the most cited papers that have applied TAM and, crucially, is the only highly cited paper that includes the correlation matrix of the original item-level empirical data. Having the original correlation matrix allows for the comparison of previous empirical data to the lexical closeness data. We perform that comparison in Section 5.2 where we show the results side by side and, in Section 6, where a p-value comparing the results is produced. Malhotra, Kim, and Patil (2006) also used the same correlation matrix and concluded that the inevitable common method bias in those data did not change the supported model.

We started the analysis we report in this section by replicating the analysis as done in Davis' (1989) TAM study 2 (the one with six PU items and six PEOU items) and then augmented that analysis with CBSEM in Section 5.2. We did these analyses on both the original data available in Gefen et al. (2003) and the two lexical closeness datasets. We performed the analyses separately for each corpus. Table 4 and Figure 4 show the business corpus PCA results after a varimax rotation. The PCA again identified three factors with eigenvalues above 1 (the top four eigenvalues were 8.656, 2.333, 1.509, and .515). Cronbach's alphas were.98 for PU, .98 for PEOU, and.68 for intended use. We bold the loading pattern to emphasize it. Table 5 and Figure 5 show the news corpus PCA results after a varimax rotation. The PCA identified three factors with eigenvalues above 1 (the top four eigenvalues were 8.504, 2.386, 1.611, and .474).

[12] The two corpora came from two distinctly different sources, and so we expected them to differ because word associations should differ across contexts. We tested that by comparing the covariance matrices in CBSEM. As expected, every covariance was significantly different between the two groups at a p-value level of less than .0001. Further, the comparison of the two overall matrix patterns showed a significant chi squared of 1390.74 with 120 df and a p-value of less than .0001.

Cronbach's alphas were .98 for PU, .97 for PEOU, and.69 for intended use. The results across corpora support the expected measurement model even without dropping any items[13].

**Table 4. PCA with Varimax Rotation on the Business Corpus**

| | Factor 1 | Factor 2 | Factor 3 | Com |
|---|---|---|---|---|
| **EOU6** | **0.93770** | 0.28535 | -0.05409 | 0.964 |
| **EOU4** | **0.93394** | 0.28225 | -0.04925 | 0.954 |
| **EOU1** | **0.91394** | 0.32340 | -0.04063 | 0.942 |
| **EOU3** | **0.90629** | 0.30586 | -0.04587 | 0.917 |
| **EOU5** | **0.88723** | 0.28552 | 0.11815 | 0.883 |
| **EOU2** | **0.86645** | 0.28149 | -0.03442 | 0.831 |
| **PU3** | 0.30994 | **0.92906** | -0.00618 | 0.959 |
| **PU4** | 0.29457 | **0.92423** | 0.06479 | 0.945 |
| **PU1** | 0.31657 | **0.92200** | -0.05811 | 0.954 |
| **PU5** | 0.29537 | **0.90164** | 0.02248 | 0.901 |
| **PU2** | 0.28862 | **0.88176** | 0.05584 | 0.864 |
| **PU6** | 0.26012 | **0.87106** | 0.13419 | 0.844 |
| **USE2** | -0.02114 | 0.00544 | **0.88064** | 0.776 |
| **USE1** | -0.03483 | 0.09151 | **0.86867** | 0.764 |

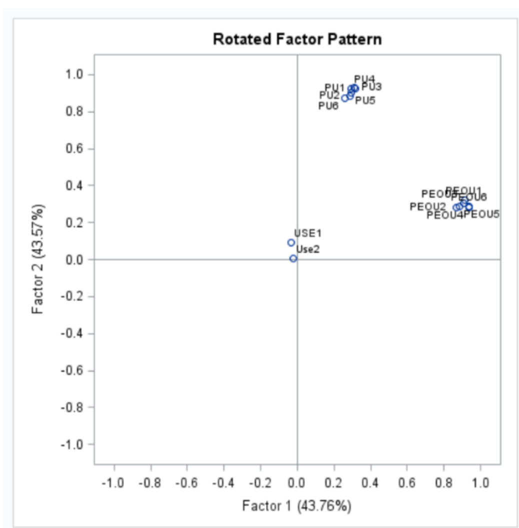



**Figure 4. PCA Item Loading Pattern Business Corpus**

[13] Because the PCA results could possibly reflect an inflated lexical closeness (this could be due to the fact that all the PU items included the words CDs and books), we redid the LSA analysis and the subsequent PCAs on the same items but excluding the words CDs and books. The results, shown in Appendix C, show equivalent patterns in Tables C1 and C2 and Figures C1 and C2. Cronbach's alphas were .97 for PU, .98 for PEOU, and .70 for intended use in the business corpus and .98, .97, .71, respectively, in the news corpus. These results support the expected measurement model with both corpora.

**Table 5. PCA with Varimax Rotation on the News Corpus**

| | Factor 1 | Factor 2 | Factor 3 | Com |
|---|---|---|---|---|
| **PU3** | **0.93852** | 0.29082 | -0.03095 | 0.966 |
| **PU4** | **0.93680** | 0.29603 | 0.03382 | 0.966 |
| **PU1** | **0.93067** | 0.30099 | -0.11042 | 0.969 |
| **PU5** | **0.92289** | 0.28080 | -0.05562 | 0.934 |
| **PU2** | **0.90588** | 0.27576 | 0.03922 | 0.898 |
| **PU6** | **0.89460** | 0.24912 | 0.09196 | 0.871 |
| **PEOU6** | 0.26997 | **0.94152** | -0.02946 | 0.960 |
| **PEOU4** | 0.25783 | **0.93948** | -0.02381 | 0.950 |
| **PEOU1** | 0.32578 | **0.91423** | -0.07326 | 0.947 |
| **PEOU3** | 0.30422 | **0.90328** | -0.04644 | 0.911 |
| **PEOU5** | 0.26813 | **0.88448** | 0.17078 | 0.883 |
| **PEOU2** | 0.23945 | **0.79430** | -0.09990 | 0.698 |
| **USE2** | -0.02227 | 0.00753 | **0.88791** | 0.789 |
| **USE1** | 0.01724 | -0.05872 | **0.86896** | 0.759 |

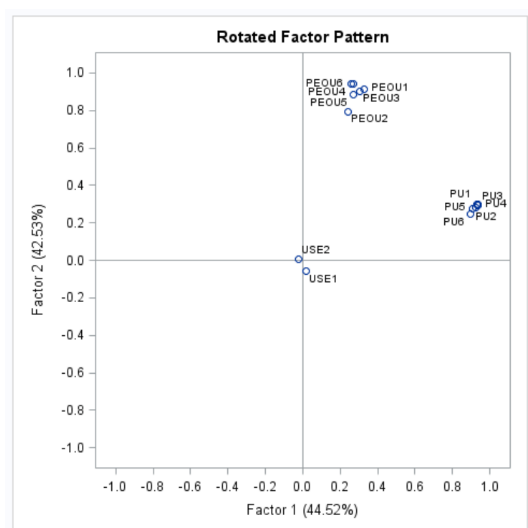



**Figure 5. PCA Item Loading Pattern News Corpus**

## 5.2. Adding CBSEM Analyses the LSA Data and its Comparison to the Questionnaire Data

We also ran CBSEM analyses on the same two lexical closeness datasets. Again, we did the analyses separately for each corpus. The CBSEM analysis combined a confirmatory maximum likelihood factor analysis of the measurement model with a structural model analysis. The measurement model provides t statistics to verify that the items load significantly on their assigned latent variables (factors in PCA are named latent variables in CBSEM terminology). Those CBSEM statistics test the expected measurement model. The structural model tests whether the latent variables support the expected model of paths among the latent variables. CBSEM also provides overall fit statistics. These overall fit statistics are important because CBSEM explicitly models all the variance in the data, including variance that is not an integral part of the model. CBSEM is confirmatory in its objective as compared to the exploratory CFA in Section 5.1. Running CBSEM means that all the variance is explicitly mapped into the model, including measurement error variance (Jarvis et al., 2003), and that any leftover variance will result in poor fit indices (Jöreskog, 1979) and with indications of unmapped measurement error (Hu & Bentler, 1998, 1999).

We conducted the analyses in LISREL. We set the sample size to 500, which corresponds to the number of data points or dimensions that the LSA analysis created. The correlation matrices appear in Appendix D. Table 6 shows the item loadings. Table 7 shows path coefficients between latent constructs 7. Fit indices for the original empirical correlation matrix in Gefen et al. (2003) were $\chi^2_{32} = 62.82$ ($p = .001$), GFI = .94, AGFI = .90, RMR = .02, NFI = .98, CFI = .99. According to current convention, these fit indices are good (Gefen, Rigdon, & Straub, 2011). The SMC values (the equivalent of an $R^2$) were .67 for intended use and .48 for PU. The original empirical correlations are available in Gefen et al. (2003). In this study, we assessed only those correlations that relate to TAM.

**Table 6. CBSEM Item Loadings**

| | Analysis of data as it appears in the correlation matrix in Gefen et al. (2003) | Business corpus lexical closeness | News corpus lexical closeness |
|---|---|---|---|
| USE1 | 1.00 | 1.00 | 1.00 |
| USE2 | 0.92** | 0.88** | 0.29 |
| PU2 | 1.00 | 1.00 | 1.00 |
| PU3 | 1.04** | 1.07** | 1.04** |
| PU4 | 1.07** | 1.07** | 1.06** |
| PU6 | 0.99** | 0.93** | 0.95** |
| PEOU2 | 1.00 | 1.00 | 1.00 |
| PEOU3 | 1.03** | 1.08** | 1.21** |
| PEOU4 | 1.00** | 1.13** | 1.29** |
| PEOU5 | 1.00** | 1.06** | 1.21** |
| ** significant at the 0.01 level | | | |

We then ran exactly the same CBSEM model specifications on the correlation matrix derived from the business corpus first and on the correlation matrix derived from the news corpus second. To allow comparison with the empirical data in Gefen et al. (2003), we dropped the same two PU and two PEOU items that they dropped[14]. Fit indices for the business corpus were $\chi^2_{32} = 250.98$ ($p < .001$), GFI = .91, AGFI = .84, RMR = .03, NFI = .96, CFI = .97. These fit indices are good (Gefen et al., 2011) and support overall model fit. The SMC values were .02 for intended use and .34 for PU, which means that the data in this corpus support the PEOU to PU path but only weakly the paths to intended use. The fit indices for the news corpus were $\chi^2_{32} = 322.73$ ($p < .001$), GFI = .89, AGFI = .80, RMR = .04, NFI = .95, CFI = .96. Again, these fit indices are good and support overall model fit. The SMC values were .00 for intended use and .30 for PU, which means that the data in this corpus support the PEOU to PU path but not the paths to intended use[15].

[14] We ran the analysis as in Gefen et al. (2003) to enable comparison of exactly the same measurement model. Running CBSEM on the lexical closeness data without dropping those four items produced equivalent results.

[15] CBSEM requires setting one of the paths from the measurement items to their corresponding latent variable to 1, which is why the paths from USE1, PU2, and PEOU2 were set to 1 and had no t-values. All the other loadings in the business corpus had significant p-values. The news corpora, presumably because its topics are less related to the organizational and business contexts of TAM, support the measurement model in only six of the seven loadings.

**Table 7. CBSEM Path Coefficients Showing the Relationships among the TAM Items in the Correlation Matrix in Gefen et al. (2003) and in the Lexical Closeness Business and News Corpora Lexical Closeness Matrices**

| To-from | Original correlation matrix in Gefen et al. | | Business corpus lexical closeness | | News corpus lexical closeness | |
|---|---|---|---|---|---|---|
| | PEOU | PU | PEOU | PU | PEOU | PU |
| Intended use | .31** | .48** | -.14 | .16** | -.09 | .03 |
| PU | .67** | | .62** | | .68** | |
| ** significant at the 0.01 level | | | | | | |

## 6 Accounting for Lexical Closeness Applying CBSEM

In Sections 4 and 5, we show that LSA lexical closeness can significantly produce the measurement model of TAM in both corpora and even parts of its structural model. This finding raises the question of whether the additional variance obtained from actual empirical data contributes significantly to improving the model. In this section, we evaluate as much by comparing the $\chi^2$ of a CBSEM model that analyzes the original empirical data with the $\chi^2$ of the same model where the empirical item loadings are constrained to be the same as the values in their corresponding lexical closeness model measures. This method is an established way to compare models across samples (Anderson & Gerbing, 1988; Gerbing & Anderson, 1988). We analyzed the same data that we analyzed in Section 5.2. Constraining item loadings in the original Gefen et al. (2003) data to be the same as those in the lexical closeness data produced $\chi2_{39}$ = 71.11 for the business corpus and $\chi2_{39}$ = 138.32 for the news corpus. The $\Delta\chi^2_7$ = 67.21 (p-value < .001) and $\Delta\chi^2_7$ = 75.50 (p-value < .001), respectively, show that the original empirical data model without constrained paths is significantly better. This result means that, while lexical closeness data produce significant results in replicating TAM (as we show in Section 5.2), the empirical data produce even better overall model fit, which the $\Delta\chi^2$ values indicate.

## 7 Discussion

### 7.1 Summary of the Comparative Analyses

The data analyses show that the lexical closeness of questionnaire items as captured by LSA on unrelated text corpora can significantly produce the measurement model of TAM and, to some degree, create some of the expected paths in the structural model. That the measurement model was supported by lexical closeness data from two completely unrelated corpora lends additional credence to this conclusion. The results imply that how people use words, which presumably reflects some aspects of their cognition, partly parallels how other people answer questionnaires. This conclusion may also suggest that one can foretell how subjects will answer questionnaires to some extent, which we can expect if LSA models some aspects of shared human cognition as widely claimed. Nonetheless, and putting the implications into perspective, empirical data collected through questionnaires significantly improved the data models, and lexical closeness data alone do not completely replicate the structural model paths. In other words, analyzing lexical closeness may allow partial replication of the measurement model, at least with TAM, but the lexical data alone may not be enough to completely recreate the expected structural model as we would expect given the influence of the setting and of subject experience in which the empirical data are collected.

Before discussing the results, we note that we need additional research before we can draw any decisive conclusions. One study may indicate an issue, but it cannot be definitive. Having said that, that the lexical closeness data analyses could replicate the measurement model, and part of the structural model of TAM, may have profound implications for both TAM and classical measurement theory. The results suggest that a possible reason why TAM has been replicated successfully across so many contexts empirically is also because of lexical closeness reasons. That is to the credit of TAM and to the methodology applied in building its measurement items. The implications for classical measurement theory, however, may be more disturbing. Constructs in classical measurement theory should relate to measurement items and to each other based on theory and the actual experience of the subjects (Anderson & Gerbing, 1988; Bollen, 1989). It should not be the case that questionnaire based models can be estimated without actually collecting data from subjects. From a classical measurement item theory perspective as applied also in

CBSEM, neither the measurement model nor the structural model should be related to how words co-occur in unrelated corpora. We discuss these implications in Section 7.2. The results may actually add a new perspective to measurement theory because measurement theory assumes that subjects answer questionnaires based on theory and the context being studied but without considering preexisting relationships among words that may embed existing knowledge through language. As one of our reviewers said, that questionnaire items measure more than only the theoretical relationships, in contrast to the view of classical measurement theory, might be disturbing to some readers, but it is to be expected if, as widely claimed, LSA models some aspects of shared human cognition. Researchers have widely established that one can prime subjects by choice of words (Cook & Campbell, 1979; Shadish et al., 2002). The application of LSA in this study suggests that one of those priming effects is because of knowledge embedded in the language. This study show: 1) the consequences of that embedded knowledge in the language, but, also, 2) the study adds a numeric verification of this phenomenon in the case of TAM and, crucially, 3) a method to statistically control for it.

## 7.2 Implication for TAM and LSA

It might not be that surprising that there is an overlap in how LSA identifies lexical closeness among a given set of keywords and how people in a pretest Q sort those same keywords as was the case with TAM. We might expect such an overlap based on what researchers have long since claimed that LSA can do (i.e., group words into synonyms). It might not be that surprising, except that those LSA lexical closeness measures produced equivalent results also to how people assessed a specific ICT based on their actual experience with it. Indeed, the data might suggest that the way people think, at least with regard to usefulness and ease of use, contributes to both 1) the lexical closeness of the words in the writing of some people about business and news that is unrelated directly to the TAM measurement items, and 2) to the answers of other people who assess a specific ICT through the TAM measurement items. And so, the results support the argument that LSA taps into underlying human lexical cognitions that people share. Those cognitions are consequently revealed, partially at least, in both writing and in assessments in questionnaires. If true that LSA taps into such underlying cognitions, then this tapping could indicate a need to account for lexical closeness correlation in current methodology and theory, including the one applied in TAM. Such a tapping also extends classical measurement theory because, according to that theory, a model should be supported because of a theory-based reason that applies to the subjects in the context being studied; it should not be supported solely because its constructs are related to language usage patterns as revealed even in unrelated corpora. According to TAM and its theory bases, TAM captures rational experience-based assessments that people have about an ICT. However, if PEOU is correlated to PU because the terms are lexically close to each other in daily language usage patterns, then testing the propositions that TAM raises about the adoption of ICT being based on rational assessments needs to include statistical controls for that lexical closeness. Presumably, LSA also captures the relationship between ease of use and usefulness because that relationship is well known enough to be reflected by newspaper stories written in the same period, for the same society, and for the same lifestyle.

We do not claim that all the answers to a TAM questionnaire are guided by mental associations based on the meaning of the words in the questionnaire items rather than by direct experience. Indeed, the empirical data contribute significantly to model fit beyond the correlations revealed through lexical closeness, and the correlations revealed through lexical closeness allow only partial replication of the structural model. Rather, the data suggest that text corpora implicitly embed information such as that revealed through lexical closeness and that this information may in some cases overlap with information other people enter in a questionnaire. Thus, the results may indicate that people do occasionally think alike and that their thoughts are reflected in common language patterns. As such, we can expect that the cognition of one group in one context, such as the people who wrote the articles in the corpora analyzed, may to some extent overlap with the cognition of another group, such as people who complete a TAM questionnaire. However, this overlap also means that there might be preexisting correlations that are plausibly unrelated to either the current sample or the theory.

On the bright side, such lexical closeness might have a positive aspect, too. If we can predict the relationship between PU and intended use based on lexical closeness in text corpora, then perhaps we can identify other words and concepts that are associated in people's cognition about ICT adoption. The key concepts in TAM were based on existing theory and could have plausibly been derived through interviews too. Conceivably, those cognitions might have been identifiable also through lexical closeness. Applying lexical closeness might, therefore, provide another method for building ICT adoption theory and possibly other theories by identifying the interrelationships among concepts even when no theory about those concepts exists. On a practical side, lexical closeness analysis may allow IT managers to identify an initial list of topics that could be important to their clients and then verify that list through interviews, which could improve service and save time by pointing managers in the right direction.

Another possible application of LSA relates to studying the dimensionality of the TAM scales. Shortly after TAM appeared, Segars and Grover (1993) questioned the dimensionality of PU by suggesting that the perceived usefulness scale should perhaps be split into perceived usefulness and perceived effectiveness. Chin and Todd (1995) challenged that suggestion. LSA could present another, possibly unrelated, side to such arguments and conceivably not only as they relate to TAM. Based on lexical closeness, LSA could perhaps provide an objective and quantitative assessment if there might indeed be reason to believe that subjects might interpret the measurement items in a questionnaire as reflecting more than one construct when the researcher intended there to be only one. Analyzing item relationships in such a way, as Larsen and Bong (2016) show, has the potential to integrate constructs across theories and enables a priori analysis before a researcher invests expensive data collection. It may even provide some indication when respondents might be assessing questionnaire items shallowly (Larsen et al., 2008a).

## 7.3 On a Broader Perspective

Classical measurement theory models the variance of measurement items in a reflective scale as comprising 1) true variance that reflects the latent construct it indirectly measures and 2) measurement error that is assumed to be extraneous, non-systemic, and random (Gerbing & Anderson, 1988; Nunnally & Bernstein, 1994). If the measurement error relates to anything except random variance, it could add inaccuracies to the interpretation of the analysis in that there may be more at play than the model and the empirical data analysis reveal, such as additional correlations among the measurement items or the way the data were collected that are absent from the model (Campbell & Fiske, 1959; Cook & Campbell, 1979; Podsakoff, MacKenzie, Lee, & Podsakoff, 2003; Shadish et al., 2002). For a detailed review, see Bollen (1989) and Podsakoff et al. (2003). It is important to note that, in classical measurement theory, extraneous variance (both systemic and non-systemic) is introduced by or related to the subjects' completing a data collection instrument (Cook & Campbell, 1979; Shadish et al., 2002). Classical measurement theory does not expect that lexical closeness derived by analyzing co-occurrences of the actual words alone in unrelated corpora may constitute significant extraneous variance. And so, while researchers have established that choice of words can prejudice and prime how subjects respond to a questionnaire item (Cook & Campbell, 1979; Shadish et al., 2002), that the words alone can determine the measurement model is new. In other words, it should not be the case that natural language usage patterns related to the keywords in a questionnaire are enough to even partly predict the empirical results of questionnaire-based research before empirical data are collected. And yet, the analyses suggest that that may partly be the case even without empirical data being collected from subjects. The above should not be interpreted as if we mean to suggest that lexical closeness might somehow replace the need to empirically collect data from subjects. Lexical closeness cannot do that because LSA, at least in its current application, cannot account for polysemy and word order (Kintsch, 2007), but it may pose an intriguing challenge to classical measurement theory. Lexical closeness shows that there is possibly more at play than classical measurement theory assumes.

Going out on a proverbial limb, it is a disturbing thought that maybe the reason that researchers often find what they are looking for is not only because they are brilliant and have come up with a compelling theory. Rather, it may be for the rather mundane reason that they share with their subjects at least some aspects of a joint cognition, a joint cognition related to language usage patterns. This reason may possibly explain why nonnative English speakers answer differently on questionnaires when responding in their native language as compared to their answers in English (Harzing, 2005). That such preexisting lexical closeness may confound measurements is clearly controversial. But, as it applies to TAM, which is perhaps the gold standard of MIS research, we introduce the results to the community in the hope of engendering and encouraging debate and more research into this topic.

## 7.4 The Sapir-Whorf Hypothesis and Classical Measurement Theory

Psycholinguistics, and specifically the weak Sapir-Whorf hypothesis, suggests that language does affect how people think (Hill & Mannheim, 1992). By logical extension, if it does, it would imply that language also affects how people respond to questionnaire items. This theory is controversial. We did not test the Sapir-Whorf hypothesis, but our findings suggest an interesting twist on it. The finding may suggest the possibility of a reverse directionality than that predicted by the Sapir-Whorf hypothesis. Rather than people being influenced by language at large, people may be incorporating into their specific use of language aspects of their cognition. And, crucially, this incorporated cognition seems to be shared across samples. That is to say, people invest into their usage of language—in this case, in their writing of text—patterns of lexical meanings that seem to predict how other unrelated people will assess an ICT. And, crucially, we can measure that overlap through LSA and tested it in CBSEM. Ergo, it may be that, rather than language determining thought, language contains in it at least some aspects of how people think and that these aspects, at least word co-occurrence patterns, apply across many individuals. As a consequence, analyzing language (as, for example, LSA does) may provide somewhat equivalent results as if asking people about their own beliefs and intentions, even about a specific ICT that are not related to the original corpora. It is as if people tend to think in the same way as other people, a supposition consistent with classical measurement theory, and that language captures these shared thoughts, a supposition that introduces new extraneous currently unaccounted for variance into classical measurement theory but that is consistent with psycholinguistics.

## 7.5 Limitations and Possible Directions Research Could Take

A possible avenue worth pursuing is to test the extent to which lexical closeness extends to actual ICT use as it relates to a specific ICT. In this paper, we show that LSA can produce measures that create the expected factorial loading patterns created by survey data on beliefs and intentions. If this conclusion applies to actual reported behavior, it would have even more potential impact.

Adding LSA analysis to questionnaire data collected in other languages and dealing with archival texts could also be an avenue worth pursuing. Doing so could verify the proposition behind LSA that it identifies human thought aspects that underlie the lexical grouping of words and that it presumably does so across languages (Islam et al., 2012).

Given the thousands of LSA studies, we might ask why researchers have not discovered the phenomenon we report here before. Previous studies that use LSA have applied lexical spaces created from small sets of documents (less than 50,000), often the ones made available at lsa.colorado.edu. This reliance on the Colorado semantic spaces may partially account for the lack of discovery given that none of those lexical spaces would have the language content to “understand” business-related questions, including the oft-used TASA (“general reading up to 1st year college”) semantic space. Research could also look into corpora of less formal English such as blog postings, social media, and so on. Presumably, those corpora may contain alternative patterns of lexical closeness.

## 7.6 Conclusion

It is an intriguing idea that it may be possible to partially replicate how subjects answer questionnaires based solely on how the items in the questionnaire lexically relate to each other in common usage patterns as expressed in unrelated texts by other people. This lexical closeness may provide some hints why TAM is consistently supported, at least in establishing the factorial validity of PEOU and PU and the correlation between them. Lexical closeness, however, also poses an issue for classical measurement theory. It may suggest that there is more at play than the model measures. Language may be recording shared cognitions across people, at least in how keywords are grouped through lexical closeness, and this shared cognition may be systemic extraneous variance. It might be an oversimplification to claim as Ecclesiastes did that: “There is nothing new under the Sun”, but, as the LSA data show, we can to some extent analyze the past as recorded in unrelated texts to predict unrelated behavioral models. We may be able to do so because LSA reveals lexical patterns that people have invested into the language, lexical patterns that are apparently shared across people and contexts.

Having shown, as is our objective in this study, that TAM has a lexical closeness aspect to it, there is now reason to study how to better refine the method. Our results show that lexical closeness has the potential to teach us more about perhaps the most important theory in the MIS discipline (certainly as measured by citations). This question is a research perspective question rather than a research paper question. We hope this paper encourages others to examine the lexical closeness of measurement items in a quantitative and replicable manner because, as is the case with TAM, lexical closeness is to be expected. As such, measurement items might be correlated due to both theoretical reasons and, as we note, also lexical closeness ones. Importantly, and recognizing that lexical closeness may be unavoidable, we also demonstrate a CBSEM method to statistically measure and control for it.

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# Appendix A: Questionnaire Items Used in TAM Study 2 (Davis, 1989)

| Item | Wording |
|---|---|
| **Intended use** | |
| U1 | Assuming CHART-MASTER would be available on my job, I predict that I will use it on a regular basis in the future |
| U2 | Assuming CHART-MASTER would be available on my job, I predict that I will use it on a regular basis in the future Likely unlikely |
| U3 | Assuming CHART-MASTER would be available on my job, I predict that I will use it on a regular basis in the future Improbably probable |
| **Perceived ease of use** | |
| PEOU1 | Learning to operate CHART-MASTER would be easy for me |
| PEOU2 | I would find it easy to get CHART-MASTER to do what I want it to do |
| PEOU3 | My interaction with CHART-MASTER would be clear and understandable |
| PEOU4 | I would find CHART-MASTER to be flexible to interact with |
| PEOU5 | It would be easy for me to become skillful at using CHART-MASTER |
| PEOU6 | I would find CHART-MASTER easy to use |
| **Perceived usefulness** | |
| PU1 | Using CHART-MASTER in my job would enable me to accomplish tasks more quickly |
| PU2 | Using CHART-MASTER would improve my job performance |
| PU3 | Using CHART-MASTER in my job would increase my productivity |
| PU4 | Using CHART-MASTER would enhance my effectiveness on the job |
| PU5 | Using CHART-MASTER would make it easier to do my job |
| PU6 | I would find CHART-MASTER useful in my job |

# Appendix B: Questionnaire Items Used in Gefen et al. (2003)

| Item | Wording | Comments |
|---|---|---|
| **Intended use** | | |
| USE1 | I would use my credit card to purchase from the online vendor. | |
| USE2 | I am very likely to provide the online vendor with the information it needs to better serve my needs. | |
| **Perceived ease of use** | | |
| PEOU1 | The website is easy to use. | Dropped by Gefen et al. |
| PEOU2 | It is easy to become skillful at using the website. | |
| PEOU3 | Learning to operate the website is easy. | |
| PEOU4 | The website is flexible to interact with. | |
| PEOU5 | My interaction with the website is clear and understandable. | |
| PEOU6 | It is easy to interact with the website. | Dropped by Gefen et al. |
| **Perceived usefulness** | | |
| PU1 | The website is useful for searching and buying CDs/books. | Dropped by Gefen et al. |
| PU2 | The website improves my performance in CD/book searching and buying. | |
| PU3 | The website enables me to search and buy CDs/books faster. | |
| PU4 | The website enhances my effectiveness in CD/book searching and buying. | |
| PU5 | The website makes it easier to search for and purchase CDs/books. | Dropped by Gefen et al. |
| PU6 | The website increases my productivity in searching and purchasing CDs/books | |

# Appendix C: Revised LSA and PCA Analyses Where PU Items Do Not Include the Words CDs or Books

**Table C1. PCA with Varimax Rotation on the Business Corpus**

| | Factor 1 | Factor 2 | Factor 3 | Com |
|---|---|---|---|---|
| **PEOU6** | 0.91466 | 0.35235 | -0.05685 | 0.964 |
| **PEOU4** | 0.91017 | 0.35134 | -0.05224 | 0.955 |
| **PEOU1** | 0.88673 | 0.39024 | -0.04512 | 0.941 |
| **PEOU3** | 0.87986 | 0.37457 | -0.04924 | 0.917 |
| **PEOU5** | 0.86341 | 0.35319 | 0.11596 | 0.884 |
| **PEOU2** | 0.84024 | 0.35032 | -0.03907 | 0.830 |
| **PU3** | 0.38917 | 0.89116 | -0.00638 | 0.946 |
| **PU4** | 0.36646 | 0.88722 | 0.07563 | 0.927 |
| **PU1** | 0.39919 | 0.88061 | -0.06731 | 0.939 |
| **PU5** | 0.35990 | 0.86137 | 0.02527 | 0.872 |
| **PU6** | 0.29314 | 0.84017 | 0.14849 | 0.814 |
| **PU2** | 0.35575 | 0.83151 | 0.06596 | 0.822 |
| **Use2** | -0.01160 | -0.00363 | 0.88319 | 0.780 |
| **Use1** | -0.04948 | 0.10764 | 0.86481 | 0.762 |

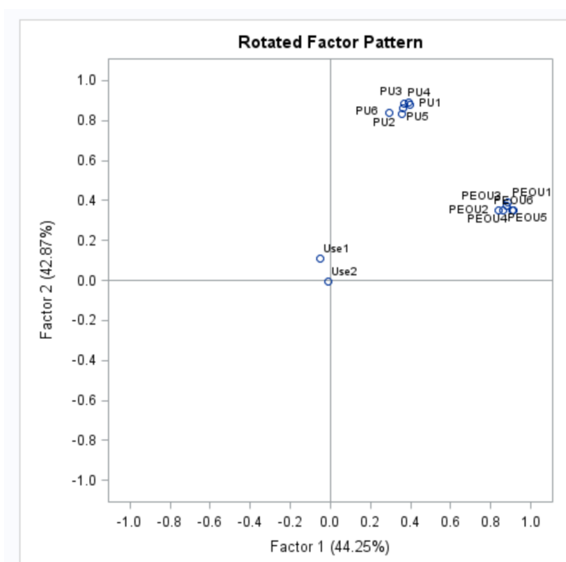


**Figure C1. PCA Item Loading Pattern After Varimax Rotation on Business Corpus**

**Table C2. PCA with Varimax Rotation on the News Corpus**

| | Factor 1 | Factor 2 | Factor 3 | Com |
|---|---|---|---|---|
| **PU3** | 0.88583 | 0.40473 | -0.0147 | 0.945 |
| **PU4** | 0.88305 | 0.40559 | 0.06579 | 0.949 |
| **PU1** | 0.87127 | 0.42686 | -0.1137 | 0.954 |
| **PU5** | 0.86676 | 0.38588 | -0.046 | 0.902 |
| **PU2** | 0.84781 | 0.36006 | 0.06848 | 0.853 |
| **PU6** | 0.84517 | 0.30818 | 0.12974 | 0.826 |
| **PEOU6** | 0.37493 | 0.90463 | -0.035 | 0.960 |
| **PEOU4** | 0.36618 | 0.90243 | -0.0289 | 0.949 |
| **PEOU1** | 0.43333 | 0.86752 | -0.0819 | 0.947 |
| **PEOU3** | 0.39686 | 0.86559 | -0.0533 | 0.910 |
| **PEOU5** | 0.37891 | 0.84435 | 0.16699 | 0.884 |
| **PEOU2** | 0.32021 | 0.76485 | -0.1048 | 0.699 |
| **Use2** | -0.0194 | 0.02002 | 0.89253 | 0.797 |
| **Use1** | 0.06649 | -0.0841 | 0.86163 | 0.754 |

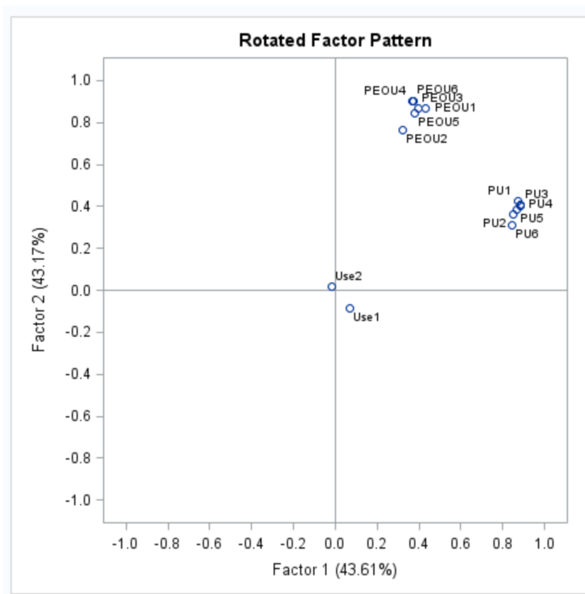


**Figure C2. PCA Item Loading Pattern After Varimax Rotation on News Corpus**

# Appendix D: Correlation Matrices of Corpora for TAM

**Table D1. Correlation Matrix of Business Corpora for TAM**

| | USE1 | USE2 | PU2 | PU3 | PU4 | PU6 | PEOU2 | PEOU3 | PEOU4 | PEOU5 |
|---|---|---|---|---|---|---|---|---|---|---|
| USE1 | 1.0000 | | | | | | | | | |
| USE2 | 0.5410 | 1.0000 | | | | | | | | |
| PU2 | 0.0850 | 0.0790 | 1.0000 | | | | | | | |
| PU3 | 0.0420 | 0.0250 | 0.9070 | 1.0000 | | | | | | |
| PU4 | 0.0960 | 0.0910 | 0.9090 | 0.9680 | 1.0000 | | | | | |
| PU6 | 0.2060 | 0.0770 | 0.7860 | 0.8470 | 0.8480 | 1.0000 | | | | |
| PEOU2 | -0.0070 | -0.0600 | 0.4840 | 0.5210 | 0.5030 | 0.4630 | 1.000 | | | |
| PEOU3 | -0.0490 | -0.0480 | 0.5370 | 0.5660 | 0.5430 | 0.4980 | 0.8550 | 1.000 | | |
| PEOU4 | -0.0520 | -0.0600 | 0.5120 | 0.5560 | 0.5340 | 0.4840 | 0.8410 | 0.9160 | 1.000 | |
| PEOU5 | 0.0650 | 0.0940 | 0.5320 | 0.5490 | 0.5500 | 0.5010 | 0.7740 | 0.8560 | 0.9120 | 1.000 |

**Table D2. Correlation Matrix of News Corpora for TAM**

| | USE1 | USE2 | PU2 | PU3 | PU4 | PU6 | PEOU2 | PEOU3 | PEOU4 | PEOU5 |
|---|---|---|---|---|---|---|---|---|---|---|
| USE1 | 1.0000 | | | | | | | | | |
| USE2 | 0.5540 | 1.0000 | | | | | | | | |
| PU2 | 0.0020 | 0.0400 | 1.0000 | | | | | | | |
| PU3 | -0.0400 | -0.0320 | 0.9240 | 1.0000 | | | | | | |
| PU4 | -0.0010 | 0.0350 | 0.9350 | 0.9750 | 1.0000 | | | | | |
| PU6 | 0.0830 | 0.0450 | 0.8380 | 0.8760 | 0.8930 | 1.0000 | | | | |
| PEOU2 | -0.0970 | -0.0770 | 0.4220 | 0.4510 | 0.4530 | 0.4090 | 1.000 | | | |
| PEOU3 | -0.0770 | -0.0400 | 0.5310 | 0.5460 | 0.5410 | 0.4880 | 0.7760 | 1.000 | | |
| PEOU4 | -0.0690 | -0.0320 | 0.4900 | 0.5180 | 0.5180 | 0.4610 | 0.7350 | 0.9030 | 1.000 | |
| PEOU5 | 0.0600 | 0.1520 | 0.5060 | 0.5130 | 0.5400 | 0.4830 | 0.6710 | 0.8280 | 0.9120 | 1.000 |

# Appendix E: LSA Process in Details as Applied

The preparation and analysis of texts has a relatively long history in MIS, including in our top journals. LSA (Deerwester et al., 1990; Dennis, Landauer, Kintsch, & Quesada, 2003) has been one of the most popular approaches; Larsen and Monarchi (2004), Sidorova et al. (2008), and Larsen et al. (2008a) have all analyzed MIS abstracts to understand the structure of MIS research and communities. Larsen and Bong (2016) applied LSA to detect construct synonymy, and Larsen, Nevo, and Rich (2008b) used LSA to examine the extent to which respondents engaged in shallow processing of a survey instrument. Going beyond use of LSA as a method to address MIS problems, Evangelopoulos et al. (2012) recommended methodological improvements to the use of LSA in the MIS discipline. Given the extensive use and description of LSA in MIS along with the large set of available software for LSA analysis, we focus here on sharing the information necessary to replicate our analysis.

## LSA Steps

### Step 1: Procuring Documents for Analysis

While no commonly agreed-on minimum set of documents required for LSA exists, the most commonly used LSA datasets generally comprise tens of thousands of documents or paragraphs. As we describe in Section 3, we used two datasets: 1) a business corpus that comprised 84,836 articles from business news outlets and 2) a news corpus that comprised 169,929 newspaper articles.

### Step 2: Creating the Term-document Matrix

In this step, we transformed the raw data into a term by document matrix that represented each document (article) as a column and each unique word that existed in any document as a row. The cells of the matrix contained the counts of how many times each word appeared in each of the documents. While it is possible to employ a stop word list of common words (low-information words such as “a” and “the”) to exclude them from the matrix, we used no such list in this project deliberately to reduce human intervention in this stage of the analysis. As is common, we ran Porter’s (1980) stemming algorithm to combine words such as “run”, “running”, and “ran” into one term. We removed numbers from the datasets along with hyphens and backslashes. The analysis was not case sensitive.

### Step 3: Weighting and Normalizing the Term-document Matrix

There are two generally acceptable formulas for weighting: TF-IDF and log-entropy. We employed log-entropy as is common outside of the MIS discipline and as Larsen and Bong (2016) did in a recent *MIS Quarterly* paper. To appropriately weigh the raw term counts as is traditional (e.g., McNamara, Cai, & Louwerse, 2007), the analysis normalized the document vectors to one. Although more recent research has found little to no effect from such normalization (Lifchitz, Jhean-Larose, & Denhière, 2009; Wild, Stahl, Stermsek, Penya, & Neumann, 2005), it provides some backward compatibility. Next, we weighted the normalized matrix using the log-entropy formula to reduce the impact of common words and to increase the impact of uncommon words. This step is considered key in making LSA work.

### Step 4: Singular Value Decomposition (SVD)

We ran SVD on each corpora dataset separately with 500 eigenvectors. The SVD algorithm, employing math known for hundreds of years but only practically possible with machine resources available in the 20th century, can be likened to a two-way principal components analysis. The relevant results of these analyses in this study are the so-called U-matrix wherein each term was endowed with a 500-dimensional vector that represents its location in what is often referred to as a “semantic space”. The first dimensions explain more of the overall variance of the original matrix and a singular value matrix (S-matrix) maintains the weight of each dimension.

### Step 5: Projecting Questionnaire Items into Semantic Space

We then subjected the survey items to the same preprocessing as the corpora, which resulted in a set of terms. The terms for each item are found in the U-matrix and retrieved with their 500-dimensional location. We then added these term vectors to create one 500-dimensional item vector that represented the location of each survey item in the semantic space. One can think of this process as “imbuing” the words in the LSA items with the lexical properties of the semantic space, much like different readers of a text will bring different interpretations to it based on their experience and language understanding. That different semantic spaces produce similar results in analyzing data shows how the commonality of language generalizes across corpora, much like it does across individuals interpreting a questionnaire.

## Step 6: Calculating Lexical Closeness

There are generally two ways to calculate lexical closeness. The most common approach is to use the cosine formula to evaluate each pair of item vectors, but, in this research, we used the Pearson product-moment correlation to better fit the logic of structural equation modeling.

# Appendix F: Sample of TAM Item Keywords as They Appear in the Corpora

LSA can project entire sentences onto a semantic space even if the original projected texts (the questionnaire items, in this case) do not appear in the corpus. To illustrate this point, we conducted two separate investigations. First, we searched for the PEOU and PU TAM items inside the articles used to create the semantic spaces. Because we found no items in their entirety, we searched for small sections of keywords inside each item. Table F1 shows a sample of the results of these searches. The brackets in the first column of Table F1 show the keywords we searched for. As Table F1 shows, even though no article contained any actual TAM item, some did contain item fragments.

**Table F1. Keyword Search**

| TAM item | Sections found | Business corpus (random sample when more than one element found) | News corpus |
|---|---|---|---|
| It is (easy to become skillful) at (using the Web site) | Bus: 7<br>News: 7 | “customers were **using the web site** to choose casket models which they would then order over the telephone" (sample from 700-word article) | “Warner Bros Records has argued that Napster.com must be shut down because its million users are **using the web site** to illegally download music without paying for it” (sample from 720-word article) |
| (Learning to operate) the (Web site is easy) | Bus: 1<br>News: 2+1 | "workers took turns debugging the new equipment and **learning to operate** it" (sample from 1,281-word article) | “below older pictures from more tranquil days like the one of Big Moe and the monkey **learning to operate** engine company automatic nozzle” (sample from 1,620-word article_<br><br>“getting groceries using the **web site is easy.** You select a category such as canned tuna and the web site offers three name brand choices” (sample from 2,126-word article) |
| The (Web site is flexible) to interact with | Bus: 0<br>News: 0 | | |
| (My interaction with) the (Web site is clear) and understandable | Bus: 1<br>New: 1 | “ninety nine percent of **my interaction with** the Bancroft family is through their representatives" (sample from 1,587-word article) | “it was the only time this had happened to me during **my interaction with** all of these services” (sample from 1,821-word article) |
| It is (easy to interact with) the Web site | Bus: 0<br>News: 0 | | |
| The Web (site is easy to use) | Bus: 0<br>News: 1 | | “the AOL music **site is easy to use** and gives surfers many reasons to visit including free sneak peeks” (sample from 1,028-word article) |
| The (Web site is useful) for (searching and buying CDs)/books | Bus: 0<br>News: 0 | | |
| The Web site (improves my performance) in CD/book (searching and buying) | Bus: 0<br>News: 1 | | “instead of offering a free jukebox program like its rivals, BuyMusic requires that you do your **searching and buying** online at buymusic.com” (sample from 1,282-word article) |
| The (Web site enables) me to search and buy CDs/books faster | Bus: 0<br>News: 3 | | “the software available for free on the Napster **web site enables** users to share songs” (sample from 1,419-word article) |

**Table F1. Keyword Search**

| | | | |
|---|---|---|---|
| The (Web site enhances) my effectiveness in CD/book searching and buying | Bus: 0<br>News: 0 | | |
| The Web (site makes it easier to) (search for and purchase) CDs/books. | Bus: 0<br>News: 1 | | "shipping clothes back and forth from stores to a central facility erased any savings, Anton says, and cleaning on **site makes it easier** to offer same day service" (sample from 1,227-word article) |
| The Web site (increases my productivity) in searching and purchasing CDs/books | Bus: 0<br>News: 0 | | |

Next, we used LSA similarity search to identify the articles that were most similar to each of the 12 TAM items. Table F2 provides the URL links to those articles in the business semantic space. We could not copy the original articles into this paper because of copyright issues. Note that we projected the TAM items onto the semantic space only after the semantic space was created based on business news articles. The table shows that there are articles that contain fragments that are somewhat close to the TAM items. (Note that we did not conduct the analysis at the level of these fragments but rather at the article level across hundreds of thousands of articles by extracting the underlying word relationships across all of them.)

**Table F2. Semantic Search**

| TAM item | Most similar business article |
|---|---|
| It is easy to become skillful at using the Web site | Bransten, L. (1998). Microsoft throws in its hand in dispute over palm devices. *Wall Street Journal.* Retrieved from https://colorado.idm.oclc.org/login?url=http://search.proquest.com.colorado.idm.oclc.org/docview/1700194112 |
| Learning to operate the Web site is easy | Bransten, L. (1998). Microsoft throws in its hand in dispute over palm devices. *Wall Street Journal.* Retrieved from https://colorado.idm.oclc.org/login?url=http://search.proquest.com.colorado.idm.oclc.org/docview/1700194112 |
| The Web site is flexible to interact with | Petersen, A. (1998). Nextel loss exceeds estimates; 360 sees profit surge. *Wall Street Journal*. Retrieved from https://colorado.idm.oclc.org/login?url=http://search.proquest.com.colorado.idm.oclc.org/docview/398822542 |
| My interaction with the Web site is clear and understandable | Young, J. (1998). Bigger ain't always better. *Forbes.* Retrieved from https://colorado.idm.oclc.org/login?url=http://search.proquest.com.colorado.idm.oclc.org/docview/194980843 |
| It is easy to interact with the Web site | Petersen, A. (1998). Nextel loss exceeds estimates; 360 sees profit surge. *Wall Street Journal.* Retrieved from https://colorado.idm.oclc.org/login?url=http://search.proquest.com.colorado.idm.oclc.org/docview/398822542 |
| The Web site is easy to use | Bransten, L. (1998). Microsoft throws in its hand in dispute over palm devices. *Wall Street Journal.* Retrieved from https://colorado.idm.oclc.org/login?url=http://search.proquest.com.colorado.idm.oclc.org/docview/1700194112 |
| The Web site is useful for searching and buying CDs/books | Hardy, Q. (1998). 3Com's sales, net plummeted in 3rd quarter. *Wall Street Journal.* Retrieved from https://colorado.idm.oclc.org/login?url=http://search.proquest.com.colorado.idm.oclc.org/docview/1699297058 |

**Table F2. Semantic Search**

| | |
|---|---|
| The Web site improves my performance in CD/book searching and buying | Young, J. (1998). Bigger ain't always better. *Forbes.* Retrieved from https://colorado.idm.oclc.org/login?url=http://search.proquest.com.colorado.idm.oclc.org/docview/194980843 |
| The Web site enables me to search and buy CDs/books faster | Young, J. (1998). Bigger ain't always better. *Forbes*. Retrieved from https://colorado.idm.oclc.org/login?url=http://search.proquest.com.colorado.idm.oclc.org/docview/194980843 |
| The Web site enhances my effectiveness in CD/book searching and buying | Young, J. (1998). Bigger ain't always better. *Forbes*. Retrieved from https://colorado.idm.oclc.org/login?url=http://search.proquest.com.colorado.idm.oclc.org/docview/194980843 |
| The Web site makes it easier to search for and purchase CDs/books. | Bransten, L. (1998). Microsoft throws in its hand in dispute over palm devices. *Wall Street Journal.* Retrieved from https://colorado.idm.oclc.org/login?url=http://search.proquest.com.colorado.idm.oclc.org/docview/1700194112 |
| The Web site increases my productivity in searching and purchasing CDs/books | Young, J. (1998, May 04). Bigger ain't always better. *Forbes.* Retrieved from https://colorado.idm.oclc.org/login?url=http://search.proquest.com.colorado.idm.oclc.org/docview/194980843 |

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