A Transdisciplinary Approach to Construct Search and Integration[1]

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ABSTRACT

Human behaviors play a leading role in many critical areas including the adoption of information systems, prevention of many diseases, and educational achievement. There has been explosive growth of research in the behavioral sciences during the past decade. Behavioral science researchers are now recognizing that due to this ever expanding volume of research it is impossible to find and incorporate all appropriate inter-related disciplinary knowledge. Unfortunately, due to inconsistent language and construct proliferation across disciplines, this excellent but disconnected research has not been utilized fully or effectively to address problems of human health or other areas. This paper introduces a newly developed, cutting edge technology, the Inter-Nomological Network (INN) which for the first time provides an integrating tool to behavioral scientists so they may effectively build upon prior research. We expect INN to provide the first step in moving the behavioral sciences into an era of integrated science. INN is based on Latent Semantic Analysis (LSA), a theory of language use with associated automatic computerized text analysis capabilities.

Keywords

Human behavior; inter-nomological network; transdisciplinary; constructs; construct validity; Stored Latent Semantic Analysis.

INTRODUCTION

For the past several decades, the behavioral sciences have grown by leaps (e.g., Roemer 1993). Despite positive growth in the volume of research in behavioral sciences, conclusive knowledge has not kept pace. Research in IS, in particular, is now being characterized as theoretically scattered (Kraemer and Dutton 1991; Orlikowski and Baroudi 1991), fragmented (Banville and Landry 1989), and chaotic (Marble 2000). We do not have the exact number of theories in social sciences but we know that there are thousands. For example, Lee, Lee and Gosain (2004) shows over two hundred theories being used in information systems research alone, and Straker (2008) lists over three hundred theories or models that have some bearing on persuasion. If researchers are not aware of closely related constructs and able to validate their level of relatedness, behavioral theories will likely continue to grow apart, leading to overlapping or identical constructs that are seldom cited or reused.

Detrimental aspects of construct plurality were demonstrated by Larsen's (2003) finding that in the IS area alone, 83 unique concepts were measured using 948 different scales and most of the research papers employing these scales did not build on existing similar scales. Furnas, Landauer, Gomez and Dumais (1987) found that different people are less than 20% likely to express the same idea using the same words. Thus, the use of different words makes it hard to find and validate the "sameness" of existing salient conceptualizations and does make alternate conceptualizations highly likely, thereby hampering scientific progress within the behavioral sciences. A major problem arises when the research the scientist should have found is complicated by synonymy and polysemy. Synonymy refers to the situation where different words describe the same concept; polysemy describes a situation in which the same word refers to multiple constructs. In the case of synonymy,

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Larsen's (2003) study found that the *ease of use* construct alone was measured using 19 differently named but highly similar scales developed over time.

We believe the status quo is no longer tolerable for any of the behavioral sciences including IS, and have developed a novel transdisciplinary tool to help researchers locate and validate existing construct measurement items. This tool has far-reaching implications for the integrity and progress of the behavioral sciences.

AN INTER-NOMOLOGICAL NETWORK (INN)

Setting

This paper outlines a new approach to gaining in-depth knowledge about interconnections between all constructs, even if they have never been tested as part of the same theory or model. Constructs are the "basic elements" of behavioral theories. Constructs are the cornerstone of the psychometric approach used throughout behavioral disciplines, and are defined as "an intellectual device by means of which one construes events. It is a means of organizing experience into categories" (Cronbach 1971, p. 464). Constructs have been developed to cover the entire spectrum of human experiences.

Once found or developed by behavioral researchers, these constructs are then woven into theories or nomological networks (Cronbach and Meehl 1955). A nomological network is defined as "the interlocking system of laws which constitute a theory" (p. 290). Constructs constitute a crucial part of these laws, and Cronbach and Meehl outlined the importance of learning more about a theoretical construct through elaborating the nomological network in which it occurs.

Suppose we are preparing to measure a construct, C. How will we know whether existing construct measurement items for construct, C' are semantically close enough to C such that construct measurement items for C' could also be used to measure C, or whether they are theoretically distinct from C? Suppose further that we can operationally define and detect applicable measurement items for a construct even when the constructs reside in different theories. Once we can detect semantically similar constructs C' for a given construct, it enables us to distinguish between construct measurement items that exhibit Convergent validity vs. those that exhibit Discriminant validity.

We can integrate constructs by specifying the interlocking system of theoretical constructs that exists across theories. We have developed a technique called Stored Latent Semantic Analysis (S-LSA), a combination of Latent Semantic Analysis and Latent Semantic Indexing (Deerwester, Dumais, Furnas, Landauer and Harshman 1990). It uses construct measurement items associated with each construct and determines, in combination with other types of textual and contextual evidence, the similarity relation among these items. Through application of S-LSA to behavioral constructs from all behavioral sciences, three types of construct relationships are uncovered:

1. Identical constructs

2. Related (likely to be correlated) constructs

3. Unrelated constructs

The number of relationships between constructs grows exponentially, thus 10,000 articles containing 50,000 constructs would have over 1.2 billion potential relationships. Integrating constructs and detecting these three types of construct relationships could revolutionize behavioral research.

Stored LSA

Latent Semantic Analysis (LSA) (Deerwester et al. 1990) is a theory-based scientific method for extracting and representing the contextual-usage meaning of words, using Singular Value Decomposition (SVD). The underlying idea of LSA is that the aggregate of all the word contexts in which a given word does and does not appear provides a set of constraints that determines the similarity of meaning of words, and sets of words, to each other (Landauer, Foltz and Laham 1998). Thus, when two terms occur in contexts of similar meaning, even in cases where they never occur in the same passage, LSA represents them as having similar meanings. This

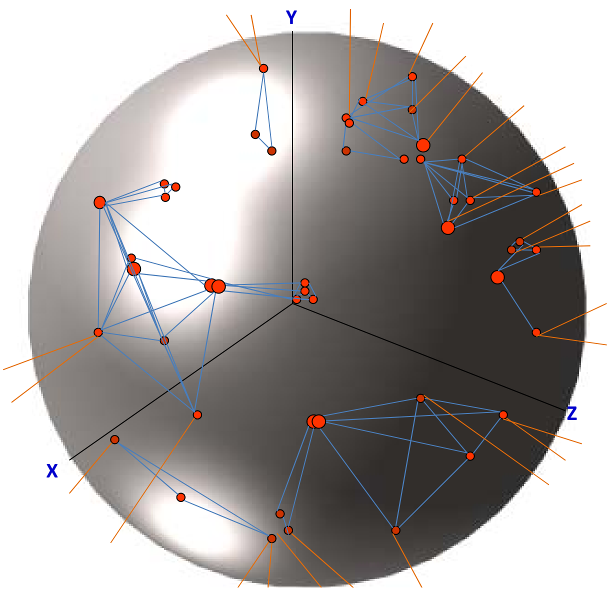

Figure 1. Representation of S-LSA Meta Semantic Space.

representation can be used to compare semantic meanings of different documents.

There are two usages for LSA, both of which start with the treatment of a set of documents to create a very sparse term-document matrix containing a weighted count of how many times a word (term) i appears inside a document j. This matrix is decomposed using Singular Value Decomposition, a mathematical algorithm similar to a two-way factor analysis, with the result being a semantic space in which every word and every document is represented by dense vectors. At this point, LSA diverges from Latent Semantic Indexing (LSI) in that LSA will generally project two or more external texts into the existing semantic space and focus on the cosines between those texts whereas in LSI one external text (or a query) is projected into the existing semantic space, and the most similar documents in the semantic space are retrieved in search-engine fashion.

LSA may be used for examination of a variety of text units, even very small ones such as individual words, whereas LSI requires paragraph size or larger texts to function properly. We aim to use LSA to examine word and sentence level texts (construct measurement items). Therefore paragraph-level texts or larger are necessary for proper synonymy and polysemy detection within the created semantic spaces for LSA.

To compile the constructs and overcome the small size of construct measurement items such as one word we use a combination of Latent Semantic Indexing (LSI) and Latent Semantic Analysis (LSA) (Deerwester et al. 1990) and for expositional ease we term it Stored LSA (S-LSA) where a rich semantic space is created based on the paragraphs in all eligible academic papers published in top journals and containing behavioral constructs. Constructs and their measurement items are projected into the above semantic space but stored as a separate meta-semantic space that is used for retrieval and semantic analysis among the constructs. The approach enables small texts to be represented by rich semantic vectors and stored for future retrieval and analysis.

Figure 1 represents a meta-semantic space with constructs (small circles, represented as the midpoint of the construct measurement items) from twelve papers in the same journal. The figure shows how constructs co-exist with other constructs within the same theory published in the same paper. This creates constellations of constructs bound together by their co-occurrence and their similarities as measured by cosines. Connecting lines between constructs represent citations in another article of the same journal. Several have citations to outside journals.

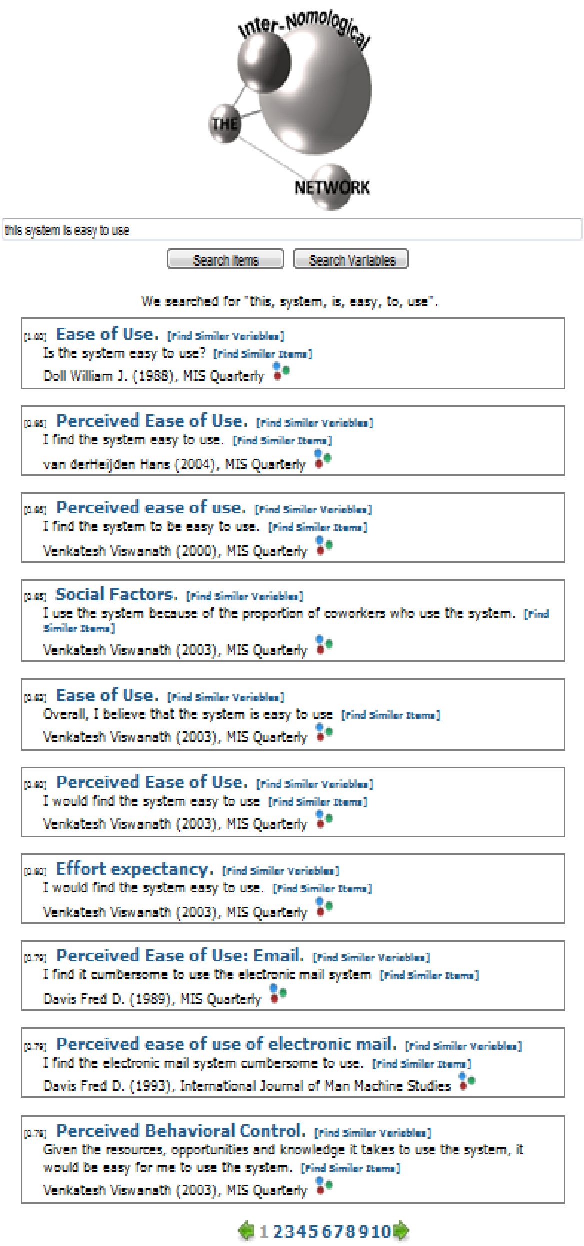

Figure 2. INN Search System Example

Case Study: Finding Relevant IS Constructs Using Proposed Approach

For demonstration purposes, a pilot version of the INN was queried for a construct measurement item “this system is easy to use” (Figure 2.) The system returns construct measurement items from a variety of constructs published in MIS Quarterly. (MISQ is currently the only IS journal in the pilot database.) It is interesting to note that the pilot INN system correctly identifies (Venkatesh, Morris, Davis and Davis 2003) Effort Expectancy as the 20th construct version of ease of use above and beyond those identified in (Larsen 2003). Further, the system suggests that an additional item, Perceived Behavioral

Control (Venkatesh et al. 2003), is also related to ease of use. With the item text, “Given the resources, opportunities and knowledge it takes to use the system, it would be easy for me to use the system,” and the construct’s origin as “the perceived ease or difficulty of performing the behavior” (Ajzen 1991, p. 188), the assertion seems reasonable at this early stage of INN development.

The search is conducted only on the text of the items currently stored in the INN, and due to the system’s synonymy features, it is also able to find reversed items such as "I find the electronic mail system cumbersome to use" (Davis 1993). In this example, the system also identifies one variable; Social Factors (Venkatesh et al. 2003) as measuring ease of use, an error due to the immature state of the INN and that this particular analytic configuration (a search engine) simplifies the complex 300-dimensional semantic space of construct measurement items into one dimension. Further development of the tool would seek to rectify such considerations.

We believe that the INN tool would enable researchers to find and understand constructs from other fields that may contradict or extend their own discipline’s closely held beliefs, help visualize how constructs cross boundaries, and may be used to enhance and extend research. For example, Figure 3 shows how a search for “trust” will find an item related to (Gefen et al. 2003) IS discipline Calculative-Based Trust construct, and also suggest that Psychology’s Perceived Integrity is related to trust (it could reasonably be argued that if respondents believe that Ballou has a great deal of integrity, they simultaneously trust Ballou). Among the nearly 100 results, a majority of which were clearly about trust or lack of trust, many had phrases such as “I feel that the other party takes advantage of people who are vulnerable” and “I feel that the other party will keep its word.” In this case, a cross-disciplinary inter-construct relationship was revealed which might not previously have been noted by researchers, and several variables with different names were found to measure overlapping constructs.

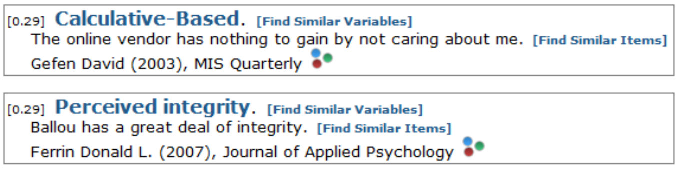

Figure 3. Search for ”Trust” (two items far down result list).

Latent Semantic Validity: Operational Definition

As demonstrated in the above case study, INN can help researchers to better leverage existing research by finding scales relevant to the constructs they want to study. While the INN infrastructure will allow identification of relevant scales based information described in the previous section, behavioral scholars need a way to test that a chosen scale does measure the construct of choice, i.e. that the scale has high construct validity (Cronbach et al. 1955, p. 290). The following describes how INN can provide this test.

A systematic method for assessing construct validity is multitrait-multimethod matrix (MTMM) proposed by Campbell and Fiske (1959). Focusing on the most commonly used parts of MTMM, we apply the following main principles: (1) measures of the same construct should be highly correlated (convergent validity), (2) measures of the constructs that should be distinguished should not be highly correlated (discriminant validity).

In this context, we argue that INN can help assess the construct validity of a construct, C by identifying a set of other constructs closely related to it using the techniques described above. The researcher might believe that one or more construct(s) in this set to be the same as C. Let us call these constructs, Ci, where i=1... m. The researcher might also find one or more construct(s) in this set that need to be distinguished from C. Let us call these constructs Dj, where j=1...n. Then for each i=1...m, we could create a Latent Semantic Validity Matrix of Ci and all Dj for j=1...n. The observation of high cosines among the traits for Ci but low cosines across the traits of Ci and Dj for each j would be additional corroborating evidence that Ci and C are the same construct and that the scale of Ci can be used to measure C.

If the researcher finds that none of the constructs retrieved by INN to be the same as C, then the researcher could comfortably focus on examining Discriminant validity for all Dj. Examining Dj for j=1..n would provide a way to assess the construct validity of the new scale. If the researcher finds no Dj from which C needs to be differentiated, then the researcher may provide such Dj’s from his or her own expertise or from the background literature.

This “semantic space” approach is based on the assumption that a semantic space, created from a large corpus consisting of texts in the relevant domain, can be viewed as the realm of observation, against which theoretical constructs can be mapped and a theory can be tested. We argue that there is sufficient evidence for this view. For example, the success that Latent Semantic Analysis has demonstrated in the tasks ranging from document retrieval (e.g., Kontostathis and Pottenger 2006), thesauri construction (e.g., Hagiwara, Ogawa and Toyama 2005), inter-language translation (e.g., Fujii and Ishikawa 2001), essay grading (e.g., Hearst 2000), text summarization (e.g., Yuan and Sun 2005), video summarization (e.g., Gong and Liu

2003), and knowledge clustering and extraction (e.g., Larsen and Monarchi 2004) indicates that the semantic spaces used represent enough knowledge about the worlds their corpus describe to be a pseudo-realm of 'observation'.

Preliminary testing done with the semantic space that our research has created also supports this assumption. Table 1 shows a Latent Semantic Validity Matrix of three scales: Job Fit, Perception of Process, and Borrowing. The table demonstrates that the pattern of cosines, produced by INN using its semantic space of scales and journal article texts, is consistent with what we would expect from correlations based on actual responses. With the first two scale samples coming from the same journal (MIS Quarterly), and the final scale coming from a journal in another field (Journal of Applied Psychology), it shows that there is no reason to believe that different scales published in the same field must be more similar than scales from different fields, indicating that we are moving towards an ability to actually bridge different fields.

Scales	**Measurement Items**	**1.**	**2.**	**3.**	**4.**	**5.**	**6.**	**7.**	**8.**	**9.**
Job Fit (Venkatesh et al. 2003)	1. Use of the system will have no effect on the performance of my job	1.00	0.71	0.71	-0.04	0.02	-0.02	0.28	0.32	0.27
	2. Use of the system can decrease the time needed for my important job responsibilities.	0.71	1.00	0.84	0.01	0.03	-0.05	0.23	0.28	0.27
	3. Use of the system can significantly increase the quality of output on my job	0.71	0.84	1.00	0.03	0.07	-0.00	0.25	0.27	0.26
Perception of Process (Chidambram 1996)	4. Were group members well committed to the goals and objectives of the group?	-0.04	0.01	0.03	1.00	0.74	0.67	0.05	0.08	0.21
	5. Did members have a strong sense of belonging to the group?	0.02	0.03	0.07	0.74	1.00	0.68	0.18	0.21	0.26
	6. Did group members recognize and respect individual differences and contributions?	-0.02	-0.05	-0.00	0.67	0.68	1.00	0.03	0.02	0.20
Borrowing (of experience during job interviews) (Levashina 2007)	7. When I did not have a good answer, I borrowed work experiences of other people and made them sound like my own.	0.28	0.23	0.25	0.05	0.18	0.03	1.00	0.88	0.69
	8. I used other people's experiences to create answers when I did not have good experiences of my own.	0.32	0.28	0.27	0.08	0.21	0.02	0.88	1.00	0.78
	9. I described team accomplishments as primarily my own.	0.27	0.27	0.26	0.21	0.26	0.20	0.69	0.78	1.00

Table 1 Cosines between Construct Measurement Items from Three Scales

The results from Table 1 are extremely encouraging given the limited work done to improve its quality. However, it could be argued these results are obvious given the clear differences between the scales. To examine INN's ability to discriminate among similarly named scales, Table 2 shows a simplified Latent Semantic Validity Matrix of seven self-efficacy scales with more than one item currently added to INN. Each cell contains the average cosine between construct measurement items for each scale, with the diagonals containing the average intra-scale cosines.

Scales	Scale 1	Scale 2	Scale 3	Scale 4	Scale 5	Scale 6
1. Self-efficacy (job setting, use of system, 4 items) (Venkatesh et al. 2003)	**0.87**	0.69	0.27	0.41	0.42	-0.04
2. Self-efficacy (job setting, use of system 10 items) (Agarwal and Karahanna 2000)	0.69	**0.90**	0.32	0.49	0.47	0.01
3. Self-efficacy beliefs (teacher setting – ability to teach students, 14 items) (Chester and Beaudin 1996)	0.27	0.32	**0.28**	0.38	0.38	0.01
4. Self-perceived Ability to Learn Mathematics (student setting, 3 items) (Skaalvik and Rankin 1995)	0.41	0.49	0.38	**0.74**	0.70	-0.05
5. Self-perceived Ability to Learn Verbal Arts (student setting 3 items) (Skaalvik et al. 1995)	0.42	0.47	0.38	0.70	**0.71**	-0.03
6. Self-efficacy for self-regulated learning (student setting, 11 items) (Zimmerman, Bandura and Martinez-Pons 1992)	-0.04	0.01	0.01	-0.05	-0.03	**0.86**

Table 2 Average Cosines Between Construct Measurement Items in Six Self-Efficacy Scales

Full results are too voluminous for inclusion in this paper, so our discussion will focus on the averaged results. The immediate positive is that self-efficacy Scales 1, 2, 4, 5, and 6 all behave as expected with high intra scale cosines. Furthermore, scales 1 and 2 are highly related (0.69) which makes sense given that they are both about self-efficacy in a job setting. In fact, it turns out that the two highest cosine items (0.83) in the two scales are almost identical:

• I could complete the job using the software package...If I had a lot of time to complete the job for which the software was provided.

• I could complete a job or task using the system...If I had a lot of time to complete the job for which the software was provided.

Other items were slightly more dissimilar, but clearly designed to measure the same underlying construct. Scales 4 and 5 were also highly related, which also makes sense given that they are the same scale used in different contexts. Due to limited data in the semantic space, INN had an inability to tell these constructs apart. It appears that with three items in each scale, those that were the same but within different contexts (I just cannot learn mathematics vs. I just cannot learn verbal arts) had high cosines (between .81 - .92.).

More importantly, scale 3 has low average intra-item cosines. The following two items from scale 3 have a 0.02 cosine, and therefore represents the most disfavorable example:

• I feel that I can make a significant difference in the lives of my students

• When it comes right down to it, most of a student's motivation depends on his or her environment so a teacher can have only limited influence

In this case, it seems likely that the INN infrastructure simply does not have enough "experience" with education-related terminology to understand that these are related. This example semantic space builds on about 1/10 the number of documents used in most well-functioning semantic spaces. Based on our own experience with scale validation, the scale seems to cast a wider net than most scales.

Excluding Scale 6, it is extremely encouraging that the inter-scale average cosines are relatively high at this early stage of the research (all between .27 and .70). These cosines are high enough that they would trigger an extra look and should become even higher as a larger semantic space is created, context is removed, etc. However, scale 6's cosines to every other scale hover around zero, which requires an in-depth examination. Consider the following construct measurement items from the scale:

•How well can you use the library to get information for class assignments?

•How well can you plan your schoolwork?

•How well can you arrange a place to study without distractions

•How well can you participate in class discussions?

Looking at these, we are actually left wondering whether these are actually self-efficacy items at all. While they are clearly intended to serve that purpose, they appear easily misinterpreted as they all could be based on external rather than internal factors.

It is important to remember that cosines are not correlations, and we will have to understand their differences to fine-tune this approach. Because the theory behind LSA as well as our experience with it both suggest that S-LSA should work well for this problem, and the early tests are quite encouraging, we remain cautiously optimistic that the INN infrastructure will help the behavioral sciences take a first step toward true transdisciplinary integration.

Our team has added over 9,000 constructs (plus another 7,600 demographic, behavior, and related variables) to an INN Infrastructure for IS, psychology, nursing, and education. We can already analyze over 40 million construct relationships. More importantly, the number of analyzable relationships grows exponentially with every added construct. Based on our estimates of the number of constructs that can be tested in any single paper, we conclude that in order to test all potential relationships between constructs now available in the INN Infrastructure, at least four million separate traditional studies would need to be conducted. Our preliminary pilot work clearly demonstrates the method's transdisciplinary nature because, using literature from these four separate disciplines, the system finds similar constructs from different disciplines to be related and different constructs from the same discipline to be unrelated.

Note that unlike such systems as Google, this system solves the problems of synonymy and polysemy, and rather than returning only those construct measurement items containing the word dependable, it finds synonymous items such as "trustworthy," "the instructor develops an atmosphere of respect and trust in the classroom," "Ballou has a great deal of integrity," etc. Even a construct like Zhang's (2007) "Our team members 'sink or swim' together" – which clearly refers to the dependability of team members – is found in spite of not containing any words directly related to dependable. For each construct measurement item retrieved, the user may examine the whole construct (name, definition, measurement items, and citations), and will in the future be able to examine visualizations of citation structures as well as semantic validities.

CONCLUSIONS

Cronbach (1987a; 1987b) made clear that measures of constructs are always open for interpretation, must be interpreted in the context of their immediate nomological network, and their interpretation must be performed not by individuals but by the larger community of researchers. Unfortunately, as it stands, the larger community has no tool enabling the collaboration and validation necessary to accomplish such a task.

Further, because science is pluralistic, different subgroups, even within a discipline, adopt different research programs, and new findings in one subfield do not necessarily translate into changes in another subfield (Cronbach 1987a). By providing a tool for researchers to find and understand results from other fields that may counter their own field's closely held beliefs, research may make larger leaps. Such access may also enable researchers and reviewers to rule out rival hypotheses.

Text analytic techniques such as S-LSA exhibit prominent advantages in that it could (1) accelerate the process to establish the inter-nomological network by taking advantage of sophisticated algorithms and computing power, (2) cover areas and disciplines much broader than traditional qualitative study by involving gradually developing information retrieval techniques, (3) combine both qualitative and quantitative information by transforming textual information into representative numerical information. Especially, given S-LSA's ability to detect semantic meaning of texts rather than their literal meanings, it could interpret and integrate behavioral constructs containing human experience more precisely and powerfully, and has the potential to one day be one of the IS discipline's most important contributions to the behavioral sciences.

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