Literature Reviewing: Addressing the Jingle and Jangle Fallacies and Jungle Conundrum Using Graph Theory and NLP

Completed Research Paper

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Abstract

Scientific advancements in all fields, including IS, are built on previous accomplishment. Identifying similar causal models is critical for synthesizing research. However, the growing knowledge repository and inconsistencies in existing literature (i.e., jingle and jangle fallacies) challenge humans' bounded rationality. Humans need supporting information systems to make a jungle of causal models amenable to analysis. This paper proposes using graph theory and natural language processing (NLP) methods to analyze knowledge networks and report similarity scores for causal models. This method builds on the first phase of the Theory Research Exchange (T-Rex) project, in which guidance on digitizing the core knowledge in publications is established. Digitizing core knowledge will provide an efficiency gain as illustrated in this paper and be a significant step forward for the knowledge economy.

Keywords: Literature review, knowledge network, causal models, jingle fallacy, jangle fallacy, jungle conundrum, graph theory, natural language processing

Accelerating Discovery

If I have seen further, it is by standing upon the shoulders of giants.

-Isaac Newton

Predominantly, scientific advancements in all fields are built on previous accomplishments (Kuhn 1962, p. 52), including IS (Webster and Watson 2002). However, when Newton was a scientist, it was a lonely discipline. He had few colleagues, and he was and still is a giant. Today, we have millions of scientists,[1] most of whom are not giants, but contributors of small pieces to the giant jigsaw of scientific discovery across myriad fields. Scientific progress requires building upon many exponentially expanding foundations, and this massive combinatorial problem of synthesizing ideas across manifold publications needs supporting technology. This problem was recognized in the middle of the twentieth century (Garfield 1955) and resulted

[1] https://en.unesco.org/node/252277

in the development of citation indices for the natural and social sciences.[2] These indices provided researchers with a wisdom of the crowd (Surowiecki 2004) perspective on what a field deems the most relevant contributions to a body of knowledge. Google Scholar is a digital enhancement and merging of natural and social science indices. While it accelerates the discovery of possibly pertinent research, Google Scholar does not encode knowledge, and scholars return to prior century practices by reading the results of their search. The failure to digitally encode knowledge inhibits the growth of many fields. Building on the shoulders of others is currently a laborious, tedious, manual task at odds with the digital age and the growth of knowledge.

As it advances, science gains in precision and explanatory power (Kuhn 1962, p. 52), both of which are usually expressed in an abstract, generic and symbolic form to internationalize comprehension and overcome the inherent ambiguity of language.[3] Each field has a set of symbols that its adherents use for exact communication (e.g., $CH_4 + 2O_2 \text{ -> } CO_2 + H_2O$). In Physics, Newton's three laws of motion are succinctly defined as causal models (e.g., $F = dp/dt$). These causal models in their various discipline-specific formalizations are the core of knowledge and the foundation of scientific reasoning (Pearl and Mackenzie 2018). We adopt Pearl's definition of causality: A causal relationship between variables X and Y exists if Y in any way relies on X for its value (Pearl et al. 2016, p. 5). Thus, a causal model is a set of these relationships. Humans are intuitive teleological theists (Kelemen 1999; Kelemen 2004). We want to see purpose, cause and effect, in our world and seek interventions (e.g., a vaccine) to desirably change effects. Yet, we have not built a universal social science repository of cause-effect relationships. Rather, scholars have to extract manually such knowledge by reading publications. This approach is ill-befitting of the digital age and a society that needs to find and implement socio-technical innovations to solve a wide range of problems, such as the UN's social development goals.

Precision and clarity are critical attributes of science, which should produce accurate conclusions, unequivocal interpretation, and reproducible processes and outcomes. Medicine and vaccine development and trials require precision and exactness to offer efficacious cures and protections. In the IS field, we seek precise definitions of concepts, rigor in theory building, and reliability and validity in empirical testing. However, the goal of precision and clarity is not always achieved. The jingle and jangle fallacies (Definitions are available in Table 1), identified as an issue a century ago (Kelley 1927; Thorndike 1904), are an important source of fuzziness in social science. They can cause fractured literature, inefficient scientific communication, and inadequate knowledge convergence (Gonzalez et al. 2020). The jingle and jangle fallacies are addressed in the IS field and other disciplines (Dann et al. 2019b; Gonzalez et al. 2020; Larsen and Bong 2016; Marsh et al. 2019; Moeini Aghkariz and Cleveland 2017). There is a recognized need to build a repository of concepts and assist quick discovery of similar and associated concepts. For example, an online platform (Inter-Nomological Network) facilitates the search for similar concepts (Larsen and Bong 2016).

While there are techniques to identify similar concepts and address inconsistency at the concept level, the relationships among concepts are overlooked, and concepts without their connections are an incomplete description of knowledge. This limits contributions at the causal model level. A significant consequence of the jingle and jangle fallacies is the **jungle conundrum**, which is the problem of identifying similar causal models from a growing knowledge repository. Identifying similar causal models is crucial in the literature review process. They inform what has been studied and possible inconsistencies in the literature and provide a foundation for scholars to synthesize knowledge. However, the bounded rationality of humans limits their ability to solve complex problems, such as literature reviewing and knowledge synthesis when there are many ambiguous interactions to consider. Relevant to the representation of causal models as graphs, cognitive research highlights three limitations of human information processing: attentional blink (the time it takes to consciously identify and consolidate a visual stimulus in visual short-term memory), visual short-term memory (the restricted amount of visual information that can be held in short-time memory), and the psychological refractory period (selecting an appropriate response for one stimulus delays the ability to select a response for a second stimulus) (Marois and Ivanoff 2005). Further, humans, as cognitive misers (Stanovich 2009), tend to think and solve problems in simple and straightforward ways rather than utilizing more sophisticated and effort-intensive schemes. These limitations highlight the need

[2] https://clarivate.com/webofsciencegroup/solutions/isi-institute-for-scientific-information/

[3] For example, the English word *set* has 39 meanings in the Oxford English Dictionary.

to leverage the power of information systems to assist in identifying similar causal models when trying to synthesize many research models. Humans need help in navigating a jungle of cause-effect graphs.

This paper presents a method to address the jingle and jangle fallacies and the jungle conundrum. Similar causal models typically cannot be easily identified as they are fragmentally embedded in publications and books. We overcome this initial barrier by encoding conceptual and procedural models as directed acyclic graphs (DAGs) (Greenland et al. 1999) and storing them in an open source labeled graph database, namely oNgDB.[4] Based on the resulting graph database, we then develop a method to measure similarity among causal models through two measures: structural and semantic similarity.

Concept	Definition
Jangle fallacy	Two identical or very similar concepts are not identifiable because they are labeled differently (Kelley 1927)
Jingle fallacy	Two concepts with identical names reference different real-world phenomena (Thorndike 1904)
Jungle conundrum	Identifying similar causal models from a growing knowledge repository
Graph isomorphism	Two graphs have a one-to-one correspondence between their nodes and there is preservation (direction) of the adjacency (McKay and Piperno 2014) (for graph illustration, see Figure 3)
Graph edit distance	The number of edit operations (e.g., addition or deletion of a vertex or an edge, or merging or splitting of vertices) necessary to make two graphs isomorphic (Gao et al. 2010) (for graph illustration, see Figure 4)
Semantic similarity	The similarity between the labels of corresponding nodes based on isomorphic bijection
Conceptual isomorphism	The extent to which two graphs are similar in terms of both their structural and semantic similarities

Table 1. Definition Table

Related Work

Digitizing Core Knowledge in Publications

This research builds on the first phase of the **T**heory **R**esearch **Ex**change (T-Rex)[5] project, in which we built a framework and guidance for coding publications as graphs (Song et al. 2021; Watson and Webster 2020). An example of a graph representation of a publication is shown in Figure 1. The various colors indicate different types of nodes, such as theories, authors, definitions (see the legend in Figure 1). Edges between nodes are labeled based on their relationships. For example, a publication is *written by* authors; a publication *defines* concepts; a publication *contains* a research model. A database of coded causal graphs is a knowledge network, and such networks quickly challenge the humans' bounded rationality (Figure 2). They require supporting information systems to make them amenable to analysis.

A coding standard is the foundation of our method as it digitizes core knowledge in publications and enables graph theory-based analysis. We have coded publications in selected *MISQ* Curations, including IT and Collaboration, Information Privacy, and Health Information Technology, and loaded them into a graph database.[6] Our graph similarity analysis uses this publicly available database.[7]

[4] https://www.graphfoundation.org/projects/ongdb/

[5] https://t-rex-graph.org

[6] https://misq.org/research-curations/

[7] https://t-rex-graph.org/database/

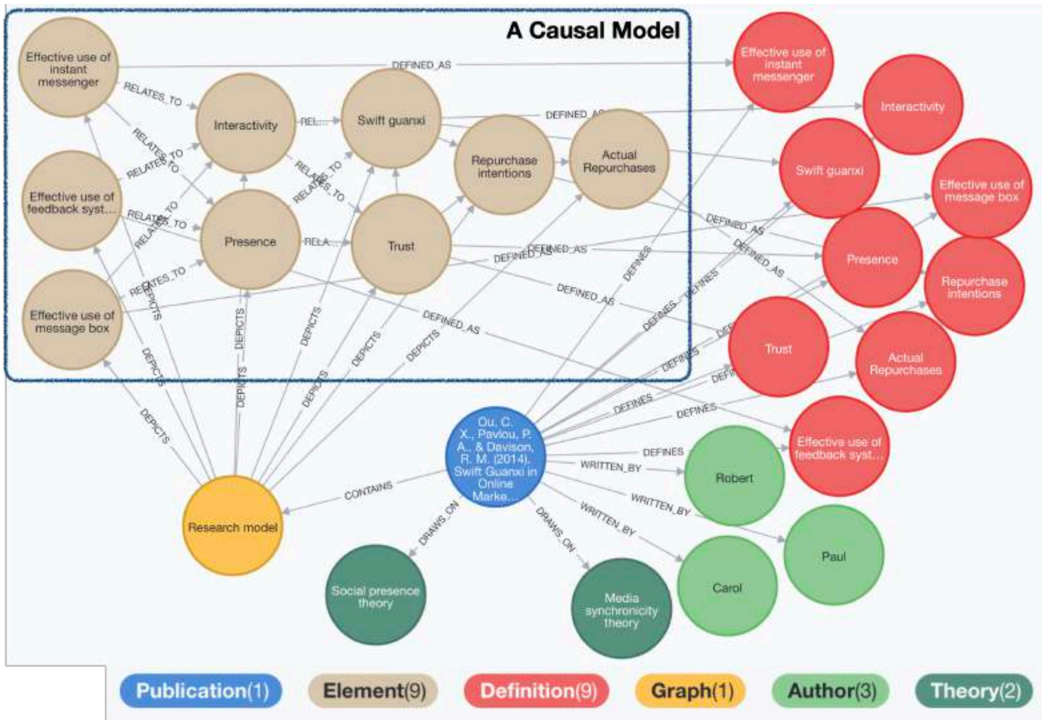


Figure 1. Graph Representation of a Publication (Ou et al. 2014)

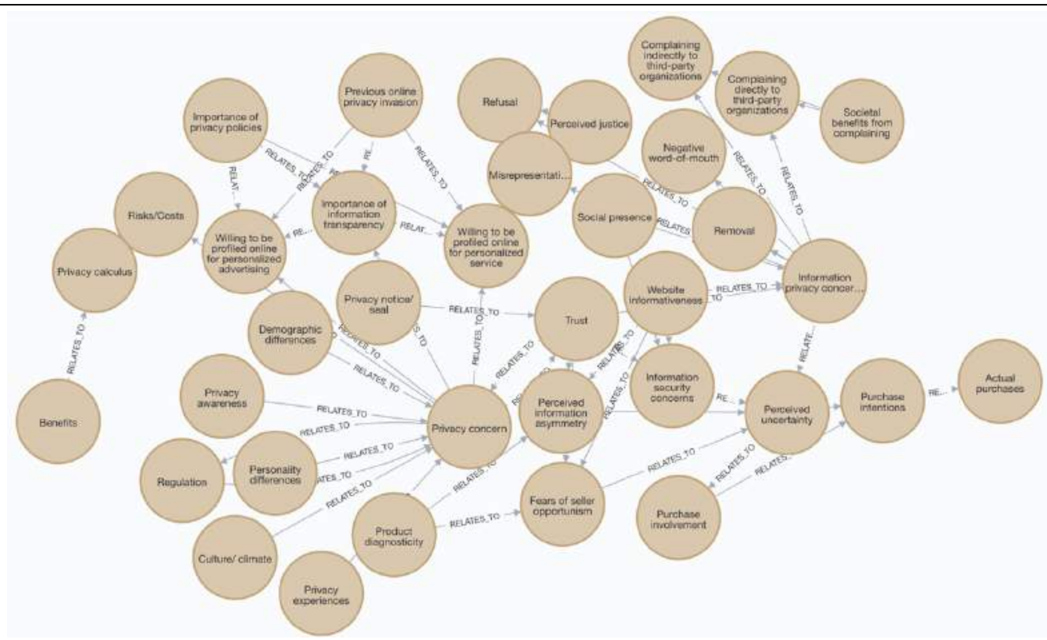


Figure 2. A Graph Network of Causal Models from Four Publications (Awad and Krishnan 2006; Pavlou et al. 2007; Smith et al. 2011; Son and Kim 2008)[8]

[8] Relationships are labelled as "RELATES_TO" with properties specified as "causal", "correlational", or "temporal" for process models. Details are available in (Song et al. 2021; Watson and Webster 2020).

The Jingle and Jangle Fallacies and Jungle Conundrum

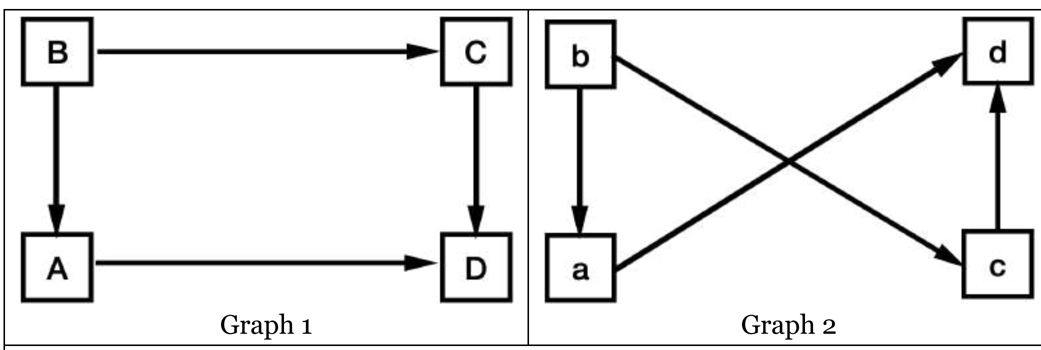
The jingle and jangle fallacies have been addressed by several scholars. The Inter-Nomological Network online platform facilitates a search of similar concepts (Larsen and Bong 2016). The online platform, Digital Scientific Knowledge Network (DISKNET) captures and accumulates concepts (including the definitions, links between concepts, and concept operationalization) in IS research and supports the exploration of relationships between concepts using machine learning techniques (Dann et al. 2019a). The TheoryOn search engine leverages current natural language processing (NLP) methods to analyze publications, facilitating the identification of model elements such as concepts, relationships, antecedents, and consequents, and the integration of corresponding theories (Li et al. 2020). A handbook was developed to review established scales and definitions of essential concepts in Marketing (Bearden and Netemeyer 1999). A common trend of these studies is to build a repository to assist the quick discovery of similar concepts using natural language processing methods. Although these concept-level approaches address concept identity issues to some extent, their applicability to causal models is limited. The relationship between concepts (nodes) is the central focus of a causal model as it graphically depicts an explanation of a phenomenon. Concepts without their connections are an incomplete description of knowledge. Therefore, graph theory-based methods are necessary to analyze the similarity of causal models and address the jungle conundrum that a scholar faces when there are many graphs to analyze and synthesize.

Graph Similarity

Identifying similar graphs (graph matching) is an important topic in graph theory (Conte et al. 2004). Graph similarity is determined by two factors: structural similarity and semantic similarity. We define an integrated measure, **conceptual isomorphism**, as the extent to which two graphs are similar in terms of both their structural and semantic similarities.

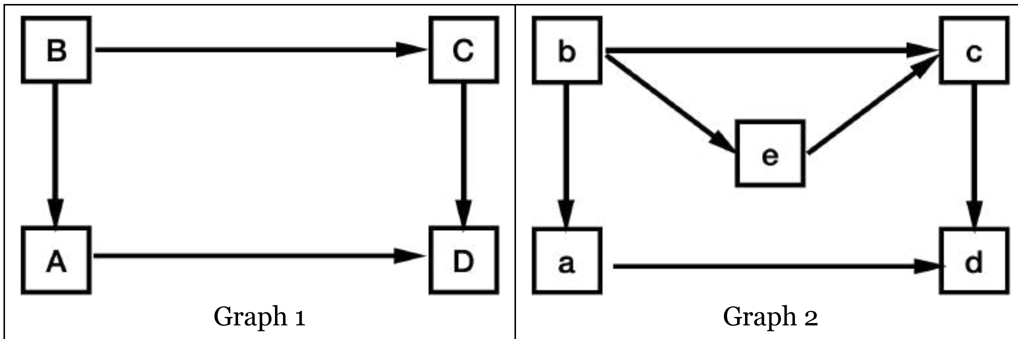
Structural similarity includes exact graph matching (graph isomorphism) and inexact graph matching (graph edit distance). Graph isomorphism requires that two graphs have a one-to-one correspondence between their nodes and there is preservation (direction) of adjacency (McKay and Piperno 2014). For example, the node bijection, one-to-one correspondence, listed in Figure 3 preserves adjacency between two graphs (e.g., B→A and b→a; B→C and b→c). The bijection indicates that the two graphs are isomorphic (i.e., having the same structure).

Graph edit distance is an error-tolerant measure of graph structural similarity, which computes the number of edit operations (e.g., addition or deletion of a vertex or an edge, or merging or splitting of vertices) necessary to make two graphs isomorphic (Gao et al. 2010). Several edit operations are necessary to make the two graphs in Figure 4 isomorphic: deleting node e and its connections with other nodes. Although by deleting node e, all associated edges are automatically deleted, the graph edit distance is three, not one, because it is a count of changes of nodes and edges rather than steps. After making such changes, there exists a bijection preserving node adjacency (i.e., A-a; B-b; C-c; D-d). A smaller number of edit operations indicates a higher similarity between two graphs. Both exact and inexact graph matching concern graph structure and together are a good measure of graph structural similarity.



Node bijection
A – a
B – b
C – c
D - d

Figure 3. Graph Isomorphism Illustration



Edit operations
Delete Node e
Delete the edge from b to e
Delete the edge from e to c
Graph edit distance is three

Figure 4. Graph Edit Distance Illustration

Semantic similarity refers to the likeness between the labels of corresponding nodes (i.e., concept name similarity) based on isomorphic bijection (i.e., the semantic similarity between A and a, B and b.).

Method

This research adopts graph theory and natural language processing methods to analyze the structural and semantic similarity of causal models to provide an integrated measure of similarity (conceptual isomorphism). An overview of the method is shown as Figure 5. First, we code individual publications (e.g., Figure 1) and a set of publications form a network of knowledge (e.g., Figure 2). The database for this paper is based on a knowledge network consisting of encoded publications in selected MISQ curations.[9]

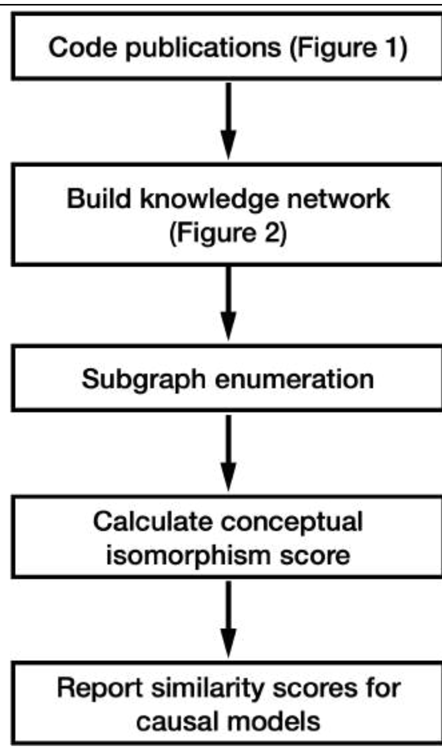


Figure 5. Method Overview

[9] https://t-rex-graph.org/database/

Subgraph Enumeration

A set of causal models from individual papers is a network of concepts (Figure 2) that expands quickly as models are added and soon overwhelms human's pattern matching skills. To identify similar causal models in terms of graph structure, we need to compute the conceptual isomorphism among a set of causal models. Therefore, we need to first enumerate all connected subgraphs in a knowledge network. We do not limit our analysis to subgraphs from each paper but consider the knowledge network formed by multiple publications on a phenomenon or theme. Therefore, the enumerated subgraphs are formed from concepts represented by graphs in different publications.

Subgraph enumeration is a computationally challenging task (Wernicke and Rasche 2006). Algorithm refinement can improve the speed, but only to some extent. As the size of a graph increases, the number of its subgraphs increases exponentially (Grochow and Kellis 2007). The on-line encyclopedia of integer sequences offers a good example of how quickly the number of subgraphs increases.[10] Large enumerations require the computational power of a high-performance computer cluster. We adopt a depth-first-search enumeration algorithm to find all connected subgraphs, as it is faster than most state-of-art algorithms (Skibski et al. 2019).

Structural Similarity

Structural similarity is based on graph isomorphism and graph edit distance. To bound the measure in a reasonable range, we divide it by the total of the maximum number of edges of two graphs and that of nodes. The ratio, when subtracted from one, provides a structural similarity measure in the range 0 to 1, with larger values indicating higher similarity.

$$Structural\ similarity = 1 - \frac{Graph\ edit\ distance}{\max(V_1,V_2)+\max(E_1,E_2)}$$

where V_i denotes the number of nodes in Graph i (i=1,2) and E_i denotes the number of edges in Graph i. If two graphs are isomorphic, the graph edit distance is zero and the structural similarity measure is 1. If two graphs are not isomorphic, adjacency preserving bijection is used to compute the number of transformational edit operations. For example, Graph 1 and Graph 2 (Figure 4) are not isomorphic, but they have the same structure after deleting node e and its connections with other nodes. The bijection between the two graphs is A-a; B-b; C-c; D-d; e-Null (Graph edit distance = 3 and structural similarity = 0.727). Our analysis of graph isomorphism, edit distance, and adjacency preserving bijection is based on the VF2 algorithm, which is a widely adopted efficient approach (Cordella et al. 2004).

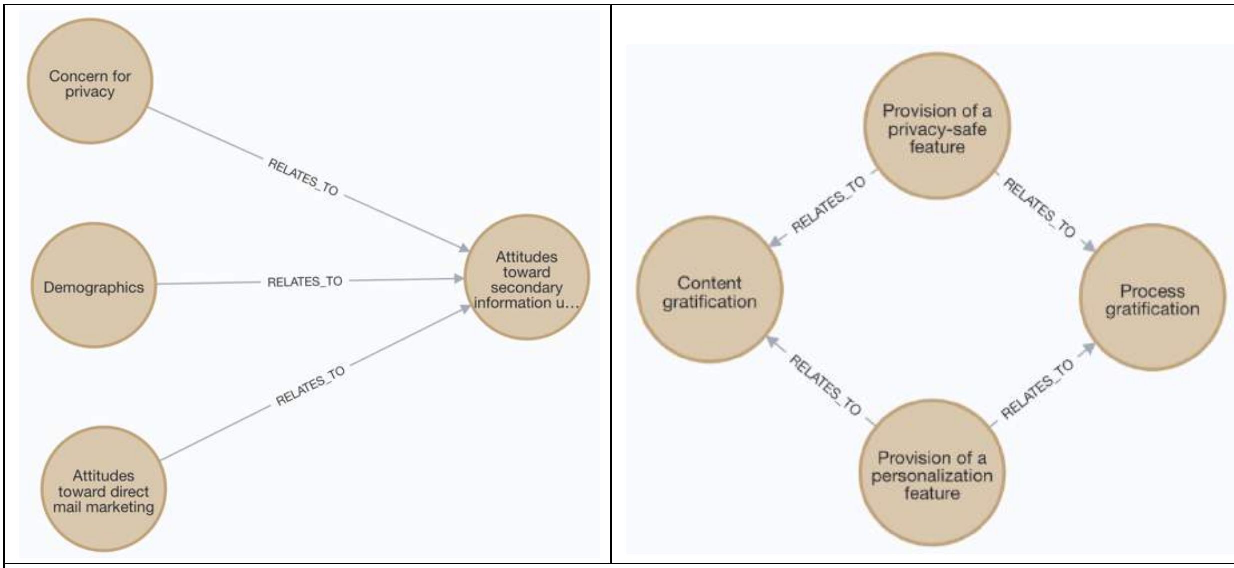
Examples of Structural Similarity

In the context of causal models, a graph structure represents relationships and causality flow among concepts. The following are examples of identical (Figure 6), similar (Figure 7), and different graph structures (Figure 8).

[10] https://oeis.org/A125207

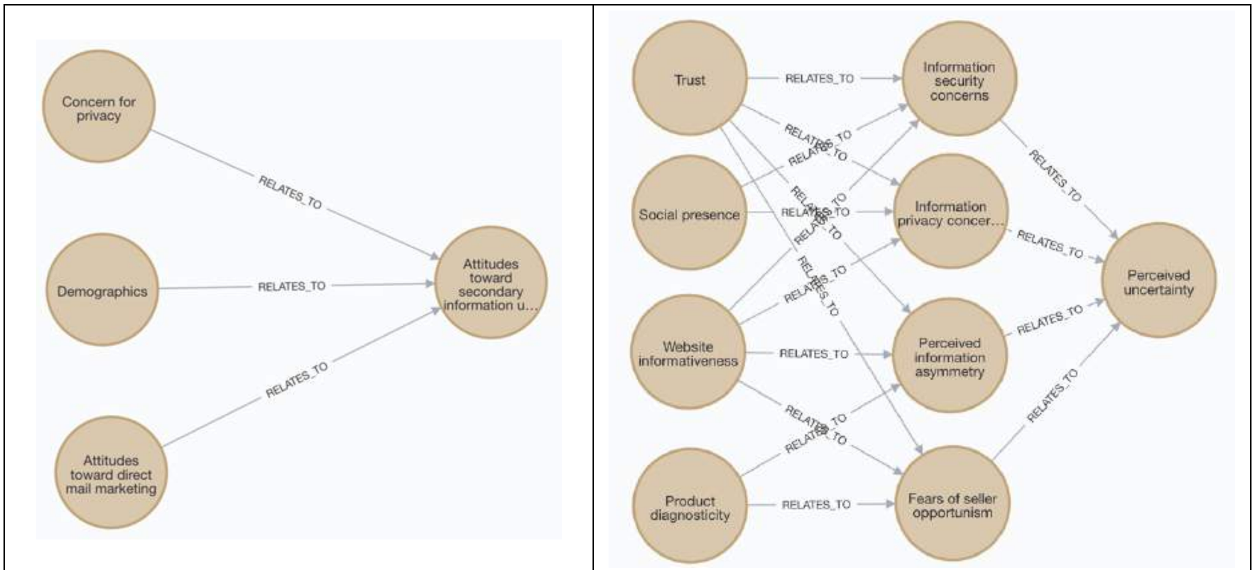
Isomorphic graphs (Graph edit distance = 0; structural similarity =1)

Figure 6. High Structural Similarity Example



Similar graph structures (Graph edit distance = 3; structural similarity =0.625)

Figure 7. Medium Structural Similarity Example



Different graph structures (Graph edit distance = 22; structural similarity=0.12)

Figure 8. Low Structural Similarity Example

Semantic Similarity

Several different algorithms can be used to measure semantic similarity, including string-based similarity, corpus-based similarity, and knowledge-based similarity (Gomaa and Fahmy 2013). String-based similarity measures operate on string sequences and character composition (Gomaa and Fahmy 2013). For example, Jaccard similarity calculates the percentage of overlap between sets (Jaccard 1912). Corpus-based similarity determines word similarity based on a corpus (Islam and Inkpen 2008). A popular corpus-based algorithm is latent semantic analysis (Landauer and Dumais 1997). Knowledge-based similarity algorithms identify the degree of similarity between words by matching the meaning of words based on semantic networks (Mihalcea et al. 2006), such as Wordnet,[11] which is a well-accepted source of word semantic meaning (Budanitsky and Hirst 2006; Mihalcea et al. 2006; Miller 1995). Wordnet performs well in an IS context (Larsen and Bong 2016). Python and R provide packages to support similarity analysis based on Wordnet.[12]

While both concept names and definitions convey conceptual meaning, at this stage, our analysis is based on concept names for two reasons. First, concept names are concise and identifiable indicators of concepts' essential meanings. Second, the analysis of concept definitions is expected to be more complex than the analysis of concept names because sentences are more than a bag of discrete words.

For illustrative purposes, we examine several concepts using the aforementioned algorithms (Table 2 and Table 3). Concepts are chosen from papers included in MISQ curations. We choose both similar ones (such as "User privacy concerns" and "Internet privacy concerns") and different ones (such as "Costs" and "Benefits") to illustrate the performance of similarity analysis algorithms. The examples demonstrate that string-based similarity algorithms are not suitable for concept similarity analysis, because they only calculate the overlap between two sets without considering the meaning of words (e.g., the similarity between "risk" and "cost" given by string-based algorithms is zero). Short text, such as concept names, usually does not have much word overlap. Corpus-based similarity requires a pre-defined corpus. Publications selected for an *MISQ* curation are considered to make significant contributions to the selected

[11] https://wordnet.princeton.edu

[12] https://www.nltk.org/howto/wordnet.html and

https://cran.r-project.org/web/packages/wordnet/index.html topics. We therefore select paragraphs defining or elaborating the selected concepts to create a corpus to illustrate the performance of these algorithms.

The knowledge-based analysis is based on Wordnet, a lexical database, which provides meanings of individual words, as the basis for semantic similarity measurement. However, concept names often are compound nouns, such as technology acceptance, information security, and system usage. The interpretation of compound nouns is an important problem in natural language processing (Kim and Baldwin 2007). Words in compound nouns are often characterized as a head-modifier relationship (Clark and Berman 1987), where the head is defined as constituent of an endocentric construction that, if standing alone, could perform the syntactic function of the whole construction (Crystal 2011). In the case of information security, the head is security, and the modifier is information. A fine-grained taxonomy of compound noun relations serves as a solid reference for identifying the head noun in compound nouns (Tratz and Hovy 2010). According to this taxonomy, the last noun in most cases is the head (e.g., security in 'information security') and the preceding nouns (e.g., information) add domain specificity or narrowing of the head noun's applicability. Without the modifier, the head of a compound noun is still able to convey the central meaning. Therefore, when concept names are compound nouns, we measure semantic similarity based on the head noun.

Another challenge we had with Wordnet analysis is that the relevant R function can only calculate the similarity between words within the same syntactic categories (e.g., nouns vis-à-vis nouns, verbs vis-à-vis verbs), but our analysis often requires comparing words of different syntactic categories (e.g., verbs vis-à-vis nouns), such as "complain" vis-à-vis "justice". To address this issue, we use Wordnet to search for all the derivationally related forms[13] (i.e., terms in different syntactic categories that have the same root form and are semantically related) of a word. We chose the most frequent noun as a replacement (e.g., "complaint" for "complain") for the similarity measure. Wordnet's definition of concepts is shown in Table 3. These examples illustrate that some head words, such as 'concerns' are generic, and it is our plan to develop a pre-processing algorithm to remove such broad terms, so the comparison in the first row would be between 'Internet privacy' and 'User privacy'.

Concept 1	**Concept 2**	**String-based (Cosine; Jaccard)**	**Corpus-based (Latent semantic analysis)**	**Knowledge-based (Wordnet)**
Internet privacy concerns	User privacy concerns	0.667	0.999	1
Information privacy concerns	Privacy concern	0.408	0.998	1
Risks	Costs	0	0.998	0.167
Trust	Work overload	0	0	0.133
Costs	Benefits	0	0.615	0.308

Table 2. Examples of Algorithm Performance for Semantic Similarity

We compute semantic similarity based on node bijection (concept mapping) using structural similarity analysis and compute the average of similarity scores between all the corresponding concepts of the two causal models. The semantic similarity score is set as zero for nodes with no match (such as e in Figure 4).

Corpus-based and knowledge-based algorithms produce relatively reasonable results (see Table 2). Our analysis, at this stage, adopts knowledge-based algorithms as a starting point. However, we will continue to investigate algorithm performance. The software will have an option that allows researchers to combine the results of corpus-based and knowledge-based algorithms (Larsen and Bong 2016).

[13] https://wordnet.princeton.edu/documentation/wngloss7wn

Concept	Definition	Source
Trust	Complete confidence in a person or plan etc.	Wordnet
Cost	the total spent for goods or services including money and time and labor	
Overload	an excessive burden	
Benefits	something that aids or promotes well-being	
Concerns	something or someone that causes anxiety; a source of unhappiness	
Risks	a source of danger; a possibility of incurring loss or misfortune	

Table 3. Concepts and Corresponding Definitions

Examples of Semantic Similarity

We observe the following examples of high and low semantic similarity from the *MISQ* privacy curation.[14] Examples of concepts with high semantic similarity include: "Information privacy concerns", "Concern for privacy", "Privacy concern", "Internet privacy concerns", "User privacy concerns". Concepts with the same or very similar meanings can have various names and often do not have a definition, which highlights the need for a similarity measure. By providing researchers with a set of models containing similar concepts, we help address jungle conundrum and accelerate the literature review process. Examples of concepts with low semantic similarity include: "Actual purchases", "Perceived uncertainty", "Issue involvement", "Strain", "Social presence", "Trust".

Conceptual Isomorphism

We integrate structural and semantic similarity measures with a linear combination. Taking an average of structural similarity and node attributes similarity is a well-accepted approach in the graph theory literature (Alinezhad et al. 2020; Combe et al. 2012; Falih et al. 2017; Jia et al. 2017).

$$Conceptual\ isomorphism = \ (Structural\ similarity + Semantic\ similarity)/2$$

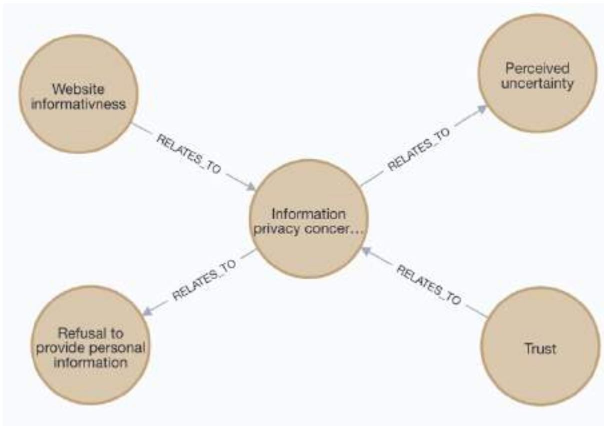
Although an average of structural and node attributes is supported in the graph theory literature, we plan to validate this approach in the IS causal model context. One way is to develop a survey asking IS scholars to access the similarity of causal models, structural similarity, and semantic similarity, which can potentially inform the weight of structural and semantic similarity and validate our choice. We can also let scholars optionally choose the weight of structural and semantic similarity.

In addition, we plan to develop a spectral measure (range from zero to one), with zero meaning two graphs are totally different and one meaning they are exactly the same. A value between zero and one indicates the likelihood that two graphs are similar, which will offer researchers a good sense of resemblance between two research models.

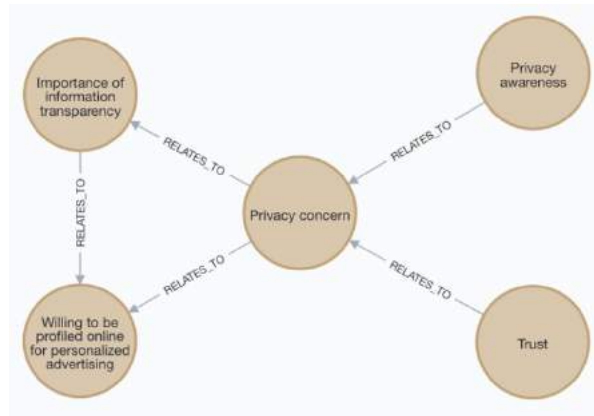
Examples of Conceptual Isomorphism

We present several examples to illustrate similar causal models (Figure 9, Figure 10, Figure 11). Identifying similar models assists the literature review process in several ways. First, it can inform the researchers of other highly relevant concepts and theories. For example, for the causal model of interest (Graph 1 in Figure 9), one of the highly similar models (Graph 2 in Figure 9) relies on three concepts that are highly relevant: "Importance of information transparency", "Willing to be profiled online for personalized advertising", and "Privacy awareness". The quick discovery of relevant concepts is especially helpful for research idea development, as it informs what the existing literature has examined regarding the idea of interest. Second, it can help identify highly similar concepts. For example, "Internet privacy concerns", "Risk beliefs", "Trusting beliefs", and "Awareness" are highly similar to "Privacy concern", "Risks", "Trust", and "Privacy awareness" respectively (Figure 11). The quick discovery of similar concepts helps identify potential jangle fallacies, i.e., whether similar concepts are indeed different or are just labeled differently.

[14] https://www.misqresearchcurations.org/blog/2017/6/30/information-privacy



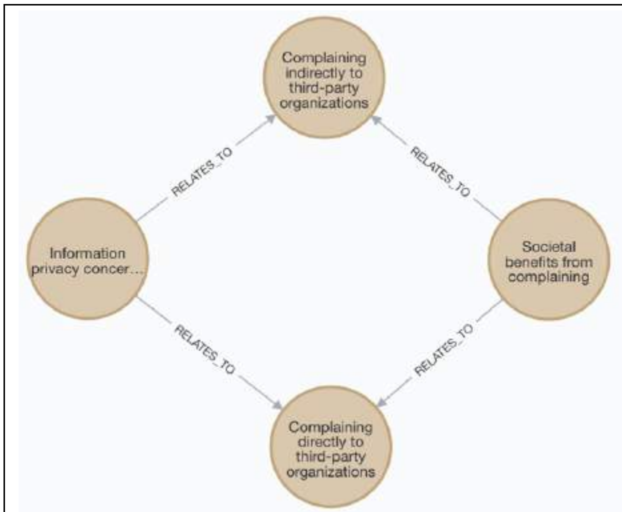
Graph 1



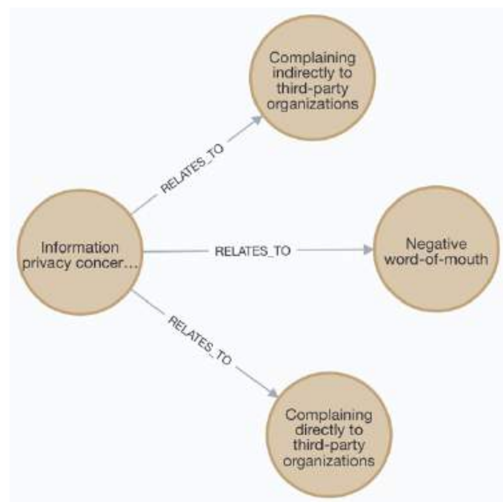
Graph 2

Conceptual isomorphism score=0.636

Figure 9. Conceptually Similar Causal Models



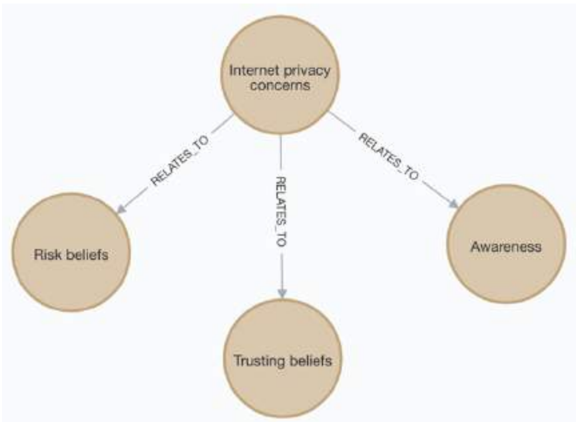
Graph 1



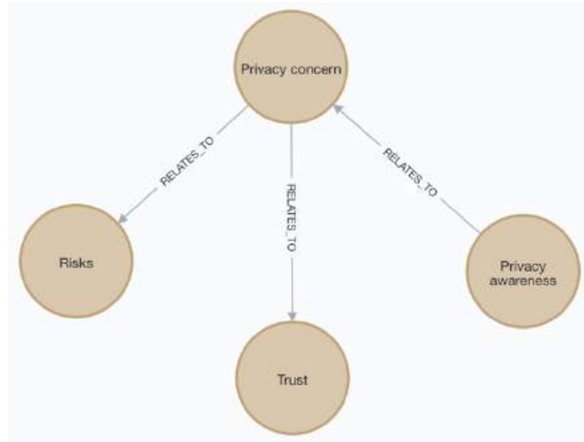
Graph 2

Conceptual isomorphism score=0.734

Figure 10. Conceptually Similar Causal Models



Graph 1



Graph 2

Conceptual isomorphism score=0.929

Figure 11. Conceptually Similar Causal Models

Implications of the Proposed Method

The proposed method assists scholars by addressing the jingle and jangle fallacies and jungle conundrum.

Implications for Jingle Fallacy

Addressing the jingle fallacy requires identifying concepts referring to different real-world phenomena but having the same or similar name. Such concepts should be connected to rather different concepts and causal models, since they have different meanings. Therefore, we can infer the similarity of concepts based on the causal models and theories with which they are connected. This tendency should be more obvious and significant with a large network of causal models. Natural language processing (NLP) methods (i.e., semantic similarity) can measure the similarity of concepts.

Implications for Jangle Fallacy

We address the jangle fallacy in several ways. First, as illustrated in the conceptual similar causal model examples, our method identifies similar concepts of interest, which provides scholars with a bag of concepts that potentially cause jangle fallacy. By examining these concepts closely, scholars can determine a concept's identity. Second, similar to the idea of addressing jingle fallacy, concepts with the same or similar meanings should be correlated with similar concepts and causal models. Therefore, with a large network of concepts, the similarity of causal models connected with certain concepts can be a meaningful measure of similarity of concepts. Third, the semantic similarity measured by NLP methods is also an indicator of concept similarity.

Implications for Jungle Conundrum

Identifying similar causal models from the exponentially expanding knowledge base is an important and understudied area. This is the jungle conundrum. Algorithms are crucial to addressing this problem, because of the growth of the research literature and the limitation of human's cognitive ability. Our method addresses this problem by 1) improving the accessibility of core knowledge through digitization; 2) developing a method to leverage the power of algorithms to analyze a knowledge network and measure causal model similarity.

Discussion

Scientific advances are built upon numerous and rapidly expanding cumulative contributions. The current approach of reading a set of possibly related literature might, at some point if not already, fails to keep up with the speed of knowledge creation and growth. Therefore, we need a supporting technology to help access collective wisdom and accumulate knowledge with a high level of clarity and precision. The foundation of the method we present is digitizing core published knowledge, which can add a level of clarity when it follows an established standard (Song et al. 2021; Watson and Webster 2020) that encourages researchers to specify critical, yet not always reported, information in publications (e.g., concept definitions). The outcome of knowledge digitization, a database of core knowledge, enables various methods to address fuzziness and inconsistency in the existing literature such as the jungle conundrum, and we propose a method to address this issue. Identifying similar causal models is an essential part of knowledge synthesis, and it requires handling equivocality in reported research. By identifying conceptually similar causal models, we provide researchers with a set of causal models for further in-depth analysis, including a close reading of an original article's text.

There are several aspects of the proposed method that we can further elaborate. First, semantic similarity analysis could be improved. Our current analysis relies on head nouns when a concept name is a phrase. We can improve this method by including the full compound nouns and completed definitions in the analysis. A possible way is combining corpus and knowledge-based methods (Larsen and Bong 2016). Second, subgraph enumeration is the most time-consuming step in similarity analysis, so adopting a more efficient enumeration algorithm can reduce computation time and improve method efficiency. However, even with efficient algorithms, graph enumeration is computationally expensive especially as a knowledge network expands. Therefore, we plan to store requested enumeration results and update them regularly based on popularity. Third, we plan to set a threshold for similar causal models to determine what results to report. To achieve this, we plan to code all papers included in MISQ curations and compute the distribution of conceptual similarity among causal models for a specified dependent variable. An experiment will be conducted to compare our method with others (e.g., TheoryOn) on their abilities to identify similar causal models. Fourth, we recognize that our analysis is bounded by the data we code. We are open to adding other data in our future work. Scalability in publication coding is essential for this project because value is achived in the whole. We will encourage authors to code their papers and ideally submit the coded model as an appendix to their journal publication when a paper is accepted, submit the paper to the community database we will establish. Finally, we acknowledge that data analytics tools generally help a researcher identify critical issues more rapidly than manual approaches, but they don't negate the need for the researcher to make judgments about the findings.

Our method should provide an efficiency gain to the IS field and other disciplines. First, it helps address jingle and jangle fallacies. Second, it helps researchers review literature by identifying similar concepts and causal models of interest and the related literature. This approach is more efficient than reading a set of papers. Third, analysis of evolution of concept relationships, research models, and theories will offer insights on the progress of IS field. As core knowledge is digitized, it will take a few queries to retrieve such information. Fourth, researchers can leverage this method to examine the inconsistency in existing knowledge and produce a more precise knowledge base for further knowledge integration and synthesis. We advocate that the IS community codes causal models as graphs and supplies the code in an appendix to their publications. As the knowledge database grows, our graph similarity method will become more valuable.

In the long term, T-Rex aims to advance the practice of knowledge synthesis by exploiting the value of digitized knowledge. With knowledge represented as graphs and stored in databases, methods, such as graph theory and network science, can be applied to generate insights for scholars and assist knowledge synthesis. The other potential use of digitized knowledge is to learn how natural and social knowledge is organized across periodicals, which is especially helpful for interdisciplinary fields, such as IS. A citation network, for example, can train algorithms to identify similarities among periodicals (Peng et al. 2020). The digitized knowledge in the form of causal models can make value-added contributions, as it offers deeper insights of the connection among knowledge beyond citations. Digitizing core knowledge will be a significant step for the knowledge economy beyond building citation indices.

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