NETWORKS OF MEANING: ADVANCING SEMANTIC NETWORK ANALYSIS FOR ORGANIZATIONAL SCHOLARSHIP

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ABSTRACT

While natural language processing (NLP) methods are increasingly adopted in organizational research, semantic network analysis (SemNA) remains underutilized. We suggest this stems, at least in part, from limitations in how semantic networks are traditionally constructed and interpreted. This paper develops a conceptual framework that introduces two key innovations designed to address these limitations, thereby revealing the promise of SemNA for organizational scholarship. First, our framework introduces two distinct types of semantic networks—*explicit usage* (rhetorical enactment based on word co-occurrence) and *latent meaning* (cognitive structure based on word embeddings)—expanding the types of meanings that scholars can represent in a semantic network. Second, we translate established social network measures into the semantic domain, shifting analysis from descriptive visualization to rigorous structural measurement. We demonstrate the framework's utility through two practical applications using quarterly earnings call data. We conclude by discussing how SemNA might be used in a wide variety of literatures interested in communication and cognition, acknowledging the method's limitations, and offering several methodological extensions. By transforming SemNA from a descriptive tool into a systematic analytic framework, this paper provides organizational scholars with a powerful new pathway for theoretical development.

INTRODUCTION

Natural language processing (NLP) is transforming organizational science. With greater access to large-scale textual data and user-friendly computational tools, many organizational scholars are exploring how NLP can enhance their research and generate new theoretical insights (Hannigan et al. 2019, Aceves and Evans 2024). By far, the NLP methods most used by organizational scholars today are dictionary-based counts (e.g., LIWC), topic models (e.g., Latent Dirichlet Allocation), and word embedding models (e.g., Word2Vec). Each method excels at different capabilities, from simplicity of use to representational richness, offering scholars a range of creative ways to map complex textual data onto organizational constructs (e.g., Aranda et al. 2024, Corritore et al. 2020, DesJardine and Shi 2021, Haans 2019).

Given this growing interest in text-based analysis, it is surprising that a fourth well-established method—semantic network analysis—has remained underutilized in organizational scholarship (see Figure 1). Semantic network analysis (SemNA) is a method that represents textual data as a network, where words are nodes connected to one another by ties (Danowski 1993, Carley and Kaufer 1993, Carley 1994). Widely used for decades in cognitive science and communications, this method has proven valuable in mapping everything from the complexities of human cognition (Siew et al. 2019) to changes in public discourse (Segev 2022). SemNA is powerful not only because it graphically represents how individual words relate to one another (Wittgenstein 1953), but also because it allows scholars to easily measure and interpret many aspects of the semantic network structure (Christensen and Kenett 2023). While several organizational scholars have started using SemNA (e.g., Jancsary et al. 2017, Giorgi et al. 2019), traditional utilization of the method remains limited in terms of how semantic networks are constructed and interpreted.

[INSERT FIGURE 1]

In this paper, we develop a conceptual framework designed to significantly enhance the method's usefulness. To do so, we develop two innovations. First, we introduce two distinct types of semantic networks: *explicit usage* (rhetorical enactment based on word co-occurrence) and *latent meaning* (cognitive structure based on word embeddings). Existing work has largely focused on explicit usage networks by capturing the co-occurrence of words in a text (e.g., Carley 1994), such as when firms are mentioned together in the same news article (Kennedy 2008) or when two words appear together in a firm's annual report (Giorgi et al. 2019). Explicit usage networks thus reveal how actors explicitly link concepts in their communication. We extend this approach by introducing latent meaning networks, which capture our implicit cognitive relationships between concepts using word embedding models (see Song and Harmon 2025). For instance, while the descriptor "visionary" appears gender-neutral on the surface, its latent semantic structure may reveal a deep-seated bias if it semantically clusters with male pronouns (e.g., "he" and "his") and remains semantically distant from female pronouns (e.g., "she" and "her"). We formalize this distinction between explicit usage and latent meaning semantic networks and explain how to construct both types of networks, thus offering a powerful expansion of the types of meaning that can be represented in a semantic network.

Second, we enhance the usability of semantic networks by translating well-established social network measures (Borgatti and Halgin 2011) into the semantic domain. Even though SemNA represents textual data as a network, existing work has largely evolved independently of network-based thinking. For example, semantic networks are often used as a descriptive tool (e.g., Jones et al. 2012) or as a way to capture the co-occurrences of just a few targeted concepts (e.g., Kennedy 2008, Giorgi et al. 2019). However, this leaves substantial textual information unexplored, limiting scholars' ability to interpret and fully utilize semantic networks once constructed. Inspired by social network scholars, we develop three ways to analyze and measure semantic networks: 1) *dyad-based measures* that capture conceptual relationships between two concepts, 2) *node-based measures* that capture local semantic structure, and 3) *network-based measures* that capture global semantic structure. We outline how these measures can be extracted from both explicit usage and latent meaning semantic networks, offering researchers new and innovative ways to extract meaning from textual data.

The paper is structured as follows. First, we provide a brief history of SemNA, tracing its roots in philosophy and cognitive science to explain its current limited usage in organizational scholarship.

Second, we introduce our conceptual framework, which integrates the two aforementioned innovations to expand how organizational scholars might construct and utilize semantic networks. Third, we provide two practical applications using earnings call data—tracking the evolution of "AI" and measuring implicit gender bias—to demonstrate how this approach yields structural insights that other NLP methods overlook. Finally, we discuss how SemNA might be used by scholars in various literatures interested in communication and cognition, followed by a discussion of the method's limitations and future extensions.

A BRIEF HISTORY OF SEMANTIC NETWORK ANALYSIS

A Network Perspective of Language

Long before semantic network analysis was developed, philosophers established the idea that meaning exists within networks of relationships rather than in isolated words. Early structuralists, most notably Saussure (1916), argued that words derive significance only through their relationships with other words. Pragmatists like Dewey (1932) and Peirce (1934) built on this idea, noting that meaning is embedded in chains of relationships rather than one-to-one correspondences. This relational view was expanded further by Wittgenstein (1953), who famously asserted that "the meaning of a word is its use in the language" (p. 43), emphasizing the idea that meaning is not a fixed definition, but rather, derived from the surrounding semantic context (see also Quine 1960).

These philosophical insights were eventually translated into cognitive science with Quillian's (1966) groundbreaking doctoral dissertation on semantic memory. This work, along with others (e.g., Quillian 1967), proposed that human memory could be represented using networks. Quillian envisioned a structure where concepts in an actor's memory (e.g., "canary" and "bird") are represented as nodes connected by different types of relational links (e.g., "is a"), creating what he called a "semantic network." This conceptual model portrayed semantic memory as an interconnected web where meaning is distributed across a network rather than contained within individual concepts. Quillian's innovation was significant because it provided a concrete, implementable network-based structure for representing the relational nature of meaning that philosophers had theorized decades earlier.

Quillian and his colleagues then developed ways to experimentally test these ideas to see if the way people retrieved information from memory aligned with predictions grounded in semantic network structures. Collins and Quillian (1969), for example, showed that the greater the semantic distance between concepts (e.g., when a concept was located at a different level of abstraction), the more time participants needed to verify the relationship. Collins and Loftus (1975) built on this insight to demonstrate that concepts, once activated, flowed through semantic networks. For instance, when the concept of "ambulance" is activated, it spreads to different clusters of related concepts, such as "siren" (e.g., a feature of ambulances), "emergency" (e.g., what ambulances respond to), or "hospital" (e.g., where ambulances go). Taken together, these early papers offered preliminary evidence that human cognition and knowledge could be represented as a network with varying degrees of associative strength between concepts.

Development and Applications of Semantic Network Analysis

Building on these foundations, the interdisciplinary work of Carley and Danowski in the 1980s and 1990s then laid the groundwork for SemNA as it is understood today. Conceptually, these scholars expanded the application of semantic networks beyond individual semantic memory, demonstrating how these networks could map shared mental models within teams (Carley 1997), collective cultural beliefs (Carley 1994), and public discourse (Danowski 1993, Carley and Kaufer 1993). Equally significant were their methodological contributions. For example, they developed systematic techniques for extracting words from text, determining proximity between words and mapping these relationships in a network structure to aid visualization (Danowski 1982, Carley 1993). These innovations transformed SemNA from a conceptual model into an analytical approach that would be picked up across multiple domains.

In cognitive science, SemNA became a powerful tool for understanding mental processes (for reviews, see Siew et al. 2019, Christensen and Kenett 2023). Developmental psychologists showed how the structure of semantic networks evolves across one's lifespan (Dubossarsky et al. 2017, Wulff et al.

2022), and clinical psychologists have used semantic networks to conceptualize mental disorders as networks of related symptoms (Borsboom and Cramer 2013, McNally et al. 2015). Extending Quillian's foundational work on semantic memory, cognitive psychologists have also developed metrics for quantifying the distance between semantic concepts (Kenett et al. 2017) and applied these techniques to studying verbal fluency (Lerner et al. 2009, Kim et al. 2019) and measuring cognitive abilities (Rastelli et al. 2020), finding, for example, that creative individuals possess richer and more flexible associative networks than less creative individuals (Kenett et al. 2014, Kenett and Faust 2019).

More recently, SemNA has started to inform research in sociology (Goldberg and Singell 2024). One application has been to use SemNA to map out and compare people's beliefs. For example, scholars have used this method to compare the different schemas of liberals and conservatives (Hunzaker and Valentino 2019), document people's attitudes towards other groups (Brensinger and Sotoudeh 2022), and trace shifts in people's positions on contentious issues (Gray and Cointet 2023). SemNA has also been used to map out the diffusion of ideas. Goldberg and Stein (2018), for example, used SemNA to capture how people interpret others' actions, while others have used SemNA to measure the novelty, prominence, or embeddedness of a new idea to assess its likelihood of being adopted (Zhou 2022, Cheng et al. 2023).

In organizational scholarship, the use of SemNA is still in its infancy. Most applications have focused on mapping explicit usage, such as how the co-occurrence of words gives significance to a particular idea (Giorgi et al. 2019, Santana and Kim 2025), a new market category (Kennedy 2008, Jones et al. 2012), or a market landscape (Jancsary et al. 2017, Höllerer et al. 2020). A smaller set of studies has begun to develop network-based measures derived from word co-occurrence to capture characteristics of focal concepts, such as the familiarity of a category label (Zunino et al. 2019), embeddedness of cultural elements (Godart and Galunic 2019), or the core-ness of a firm within a market (Claes and Godart 2025). These pioneering studies offer preliminary evidence for the promise SemNA holds for organizational scholarship.

Unlocking the Potential of Semantic Network Analysis

Yet despite this early progress, SemNA remains underutilized in organizational scholarship. We argue that this limited adoption is not due to the method's lack of theoretical utility, but instead, stems at least in part from two persistent limitations in how semantic networks are traditionally constructed and interpreted. We outline these limitations and explain how our proposed framework aims to address them.

The first limitation lies in *network construction*. Prior work has largely focused on constructing semantic networks based on word co-occurrence (e.g., Jones et al. 2012, Godart and Claes 2017, Jancsary et al. 2017). Mapping co-occurrences valuably captures actors' explicit usage of language, or the observable connections that actors forge when rhetorically enacting meaning in communication. However, explicitly linking two concepts together in language overlooks the latent meanings, or the deep, sedimented cognitive structures that organize our understanding but are rarely explicitly stated. To address this, we formalize the distinction between explicit usage semantic networks (based on co-occurrence) and latent meaning semantic networks (based on word embeddings), expanding the methodological toolkit to include the modeling of implicit cognitive structures.

The second limitation lies in *network interpretation*. Once a network is constructed, SemNA has suffered from a lack of rigorous analytical tools, often leading to the problem of interpretability. In the absence of systematic measures, semantic networks often appear as dense, visually complex structures (e.g., often referred to as "visual hairballs") that are difficult to decipher. This can lead scholars to rely on descriptive visualizations or track only a few targeted concepts in order to interpret such complexity (e.g., Kennedy 2008, Giorgi et al. 2019). We address this by translating established social network measures—such as degree centrality, brokerage, and density—into the semantic domain. We also clarify how the interpretation of each measure differs depending on whether it is applied to an explicit usage network or a latent meaning network, offering systematic guidance on how different network measures can be used in each semantic network type to capture distinct theoretical constructs. This shifts the method from a descriptive tool for visualization to a rigorous analytic framework for measuring and interpreting the structure of meaning.

SEMANTIC NETWORK ANALYSIS: A CONCEPTUAL FRAMEWORK

Our conceptual framework has two components. The first is *network construction*, which delineates between two types of semantic networks—explicit usage and latent meaning—and explaining their construction methods, similarities, and differences. The second is *network interpretation*, which introduces an innovative set of semantic network measurements that organizational researchers can employ to capture different dimensions of meaning. Together, these two components equip organizational scholars with a powerful toolkit for constructing and analyzing SemNA, revealing new ways to systematically uncover meaning in textual data along with a wide range of different theoretical questions researchers might explore.

Network Construction

Semantic networks are constructed with nodes and ties, which together form the architecture through which meaning can be represented. Importantly, what a semantic network represents—its meaning, interpretation, and usage—is a function of how it is constructed. As such, this section lays out the components of a semantic network, the different ways these components can be constructed, and the implications this has on what is being measured.

Nodes represent semantic concepts, such as an idea, entity, or attribute expressed in a text (Carley 1993). In practice, semantic concepts are typically operationalized as words (e.g., "performance," "innovation," or "Microsoft") or word phrases (e.g., "strategic planning," "social responsibility," or "Apple Inc."). For example, Kennedy (2008) used firm names mentioned in the media as nodes, whereas Godart and Galunic (2019) used stylistic elements (e.g., "colors," "patterns," "fabrics") mentioned by fashion houses in their collections. The selection of which semantic concepts to denote as nodes is an analytical decision that will shape the resulting network structure and interpretation.

Ties represent conceptual relationships between semantic concepts. Conceptually, ties are based on the proximity (or distance) between two different concepts (Carley 1993). For example, "Apple Inc." and "personal computer" are more proximal to one another and are thus likely to be connected by a tie, whereas "Apple Inc." and "fabrics" are not. Ties can be thought of in two ways. First, a tie can be explicit in spoken language when semantic concepts are talked about in conjunction with one another. For example, a news article in the 1980s might have explicitly linked the two concepts by reporting that "Apple Inc. will launch a new personal computer this year." Second, a tie can also be implicit within our extant social knowledge, instead capturing latent associations or relationships that are no longer explicitly connected in our communication. For instance, while "Apple Inc." today is obviously connected in our minds to the "personal computer," this relationship is largely taken-for-granted and, as such, the terms tend not to explicitly co-occur in textual data.

This distinction gives rise to two types of semantic networks—1) *explicit usage* and 2) *latent meaning*—which capture different aspects of the meanings embedded within textual data. Explicit usage semantic networks capture the conceptual relationships made overtly in a text. These networks represent the enactment of meaning, or the observable connections that actors forge when communicating or constructing an idea. In contrast, latent meaning semantic networks capture implicit conceptual relationships embedded within an overall text corpus. These networks capture the underlying structure of meaning, the sedimented, taken-for-granted landscape of associations that actors rarely make explicit but navigate on a daily basis. Theoretically, these two networks are dynamically related: repeated explicit enactments can become sedimented and reshape the underlying latent structure (Kennedy 2008, Green et al. 2009), while existing latent structures constrain the meanings actors can legitimately draw upon to mobilize and act (McPherson and Sauder 2013, Glaser et al. 2016).

In this section, we outline the similarities and differences of explicit usage and latent meaning semantic networks, as summarized in Table 1, as well as the key methodological decision factors when constructing both these semantic networks.

[INSERT TABLE 1]

Explicit Usage Semantic Network

Explicit usage semantic networks capture the observable ways in which meaning is articulated through language. They model the structure of discourse as it is actually used, or rather, how actors explicitly link words, ideas, or entities together in communication. By tracing surface-level co-occurrences, researchers can map how concepts are publicly connected, framed, and negotiated in text. These features make explicit networks especially useful for studying how actors construct, contest, and communicate meaning in real time, how entrepreneurs frame their ideas in investor pitches, or how new categories emerge through shifting word pairings over time. In such cases, explicit networks illuminate rhetorical structure, or the visible, enacted connections among ideas that signal how meaning is communicated and negotiated across audiences.

Input Corpus. The input corpus for constructing an explicit usage semantic network consists of the text the researcher wishes to analyze. It need not be large. What matters is that it be targeted and theoretically aligned with the research question. Kennedy (2008), for example, analyzed a corpus of press releases and media coverage to study the emergence of a new market category. Giorgi, Maoret, and Zajac (2019) used firm annual reports to examine how concepts surrounding "safety" in the U.S. automotive industry, enabling them to trace the evolving cultural meanings of legal compliance. In both cases, the corpus was delimited to the texts where relevant meaning construction unfolded.

Capturing Nodes. Nodes represent the semantic concepts that populate the network. For explicit usage semantic networks, their selection once again depends on the researcher's theoretical focus. Kennedy (2008) defined nodes as firm names mentioned in the media (e.g., "Sun Microsystems," "Apollo Computer"), treating each as a cognitive object within the emerging workstation market. Godart and Galunic (2019), in contrast, represented stylistic elements—such as "color," "fabric," or "pattern"—as nodes in a semantic network of high-fashion design, enabling them to trace how certain cultural elements gained prominence over time. The decision of what counts as a node thus reflects the level of analysis at which the researcher seeks to infer meaning (e.g., actors, ideas, or attributes).

Capturing Ties. Ties in an explicit usage network are determined by the co-occurrence of nodes within a defined textual window. The researcher must specify the context window within which two concepts are considered to co-occur (e.g., sentence, paragraph, or entire document). This methodological choice shapes the granularity of meaning captured. For instance, Godart and Claes (2017) used a narrow four-word window to the left and right of focal brand names like "Rolex" to identify semantic ties (e.g., "Rolex"–"luxury") that revealed how audiences associated brands with cultural attributes in the luxury watch market. Kennedy (2008) instead defined his window at the level of news stories, treating firms mentioned together in the same article as linked. Once the context window is determined, researchers must translate co-occurrences into network ties, either by treating co-occurrence frequency as a continuous measure of tie strength or by establishing a tie when the frequency of co-occurrences exceeds a particular threshold.

Interpretation. Once constructed, an explicit usage semantic network can be interpreted at several levels. At the broadest level, the overall network reveals how meanings are explicitly enacted through language. Within that structure, individual ties show the direct relationships actors forge between concepts, and clusters of nodes reveal recurring themes or frames that coalesce around those linkages (e.g., Kennedy's emergent "workstation" category or Giorgi et al.'s shifting association between "safety" and "cost"). These clusters help define the dimensionality of the discourse, revealing the type and diversity of conceptual domains explicitly communicated. In explicit usage semantic networks, observability is high because these co-occurrence relationships are directly visible in the text, allowing for transparent interpretation, easy replication, and comparison across studies.

Summary. Constructing an explicit usage semantic network can be as small and targeted or as large and comprehensive as the researcher desires. Because it relies on observable language use, it provides a transparent window into how meanings are enacted, negotiated, and contested through communication. For this reason, explicit usage networks are a powerful tool for examining how individuals and organizations explicitly use language and communication to construct meaning.

Latent Meaning Semantic Network

Latent meaning semantic networks capture the implicit structure within a text corpus, which are the underlying patterns of association that shape how meanings are organized and inferred, even when never explicitly stated. Rather than relying on direct word co-occurrences, these networks are derived from statistical regularities in large bodies of text, revealing the deep semantic architecture through which words acquire meaning in context. This approach shifts attention from what actors say to how language itself encodes shared understanding, allowing researchers to uncover cognitive structures that remain invisible in surface discourse. Latent networks are thus especially well-suited for exploring the taken-for-granted and often unconscious dimensions of meaning, such as revealing how cognitive schemas are embedded in language, how cognitive biases manifest, and how implicit associations persist.

Input Corpus. Constructing a latent meaning semantic network requires a corpus large enough to capture the background linguistic regularities that shape word meanings. Such a corpus provides the basis for estimating—or training—the underlying semantic structure of language. Researchers can then analyze the semantic structure of the entire training corpus (e.g., quarterly earnings calls or emails from all employees within an organization), or they can apply the semantic structure from the training corpus to a smaller target corpus that reflects a specific organizational context of interest. For example, Song and Harmon (2025) used as a training corpus all the language used by entrepreneurs and their audiences on the Product Hunt platform to identify ambiguous words, and then used that to measure the ambiguity of entrepreneurs' pitches on the platform as their target corpus.

Capturing Nodes. As with explicit networks, nodes represent semantic concepts—usually words or short phrases—but here they are embedded in a multidimensional vector space rather than a two-dimensional co-occurrence matrix. Each word's vector encodes its contextual usage across the training corpus. These vectors are typically learned through natural language processing models such as Word2Vec, GloVe, or BERT (Mikolov, Sutskever, et al. 2013, Pennington et al. 2014, Devlin et al. 2019). The advantage of this approach is that it allows meanings to emerge from the data rather than being predefined by the researcher. For instance, in Song and Harmon's (2025) analysis, each word used on the Product Hunt was represented as a vector derived from community-wide usage on the platform. This enabled them to precisely measure the representational location and, thus, semantic meaning of every word that could be used by entrepreneurs or audience members in that setting.

Capturing Ties. In a latent meaning network, ties represent semantic similarity rather than direct co-mention. The most common metric is cosine similarity between two separate word vectors, which measures the angle between them in multidimensional space. A high cosine similarity indicates that the two words occur in similar linguistic contexts and therefore share meaning. Researchers can then use this as a measure of tie strength (i.e., the higher the similarity, the stronger the tie). Another option is to create ties based on when the cosine similarity score exceeds a chosen threshold (e.g., > 0.5 on a 0–1 scale). This threshold determines network density and should be aligned with the research objective (Veremyev et al. 2019). Song and Harmon (2025), for example, used a threshold of 0.6, but demonstrated that the analysis does not change at different threshold levels. Regardless of approach, the multidimensionality of using cosine similarity for tie creation allows researchers to observe subtle gradations of meaning that explicit networks cannot capture.

Interpretation. Latent meaning semantic networks can also be interpreted at several levels. At the broadest level, the overall network reveals the underlying cognitive architecture underlying the corpus, which is the often-unspoken structure of meaning that organizes textual data across contexts. Within that structure, individual ties capture implicit associations that cohere in the collective semantic space, even when these relationships are never explicitly stated. Clusters of nodes then illuminate broader conceptual domains that emerge from these patterns of shared usage. Together, these clusters define the latent and implicit dimensionality of the semantic space that underlie language use. As a result, while latent networks reveal the tacit structures of thought that underlie language use, observability of these structures is lower because these relationships are inferred from statistical regularities rather than being directly visible in text.

Summary. Latent meaning semantic networks enable scholars to map the implicit architecture of meaning that underlies a large body of text. By representing language as a high-dimensional semantic space, they uncover associations that remain invisible in surface co-occurrence data. Such networks are powerful for studying taken-for-granted cognitive structures, shared cultural schemas, or the subtle biases and associations that shape organizational language. In this way, latent meaning networks extend the reach of semantic network analysis beyond what actors explicitly say to what to the latent categories and schema underlying a large body of texts, illuminating the deeper, often unspoken, structures of meaning that organize our thought and communication.

Network Interpretation

Once a semantic network is constructed, the next question is how it can be analyzed to uncover the meanings that lie within it. The power of representing language as a network is that meaning is not only embedded in the individual nodes (words or concepts) but also in the configuration of ties among them. Just as social networks have long been used to reveal patterns of connection, influence, and structure among actors, semantic networks allow researchers to examine how meaning itself is structured, not only locally around specific concepts but also globally across an entire corpus of discourse.

Building on social network-based thinking, in this section we translate several well-established network measures from the social to the semantic domain. Social network scholars have developed a rich toolkit for understanding the relational properties of systems, ranging from individual centrality and brokerage to the density and modularity of entire networks (Wasserman and Faust 1994, Borgatti and Halgin 2011). By translating these measures into the semantic domain, we believe that organizational scholars can move beyond simply describing which words co-occur to analyzing how concepts are positioned, connected, and organized within the broader architecture of meaning. This translation thus expands SemNA from a descriptive mapping of language to a systematic analytic framework for capturing the structure and dynamics of meaning.

We organize these measures across three levels of analysis—dyadic, node, and network—to parallel the established hierarchy in social network research. Dyad-level measures focus on the relationships between pairs of concepts and represent the traditional foundation of SemNA. Node-level measures extend the analysis to examine how individual concepts occupy distinctive positions within the semantic system (e.g., whether they serve as hubs of meaning, are embedded in tightly knit clusters, or connect otherwise separate regions of meaning). Finally, network-level measures capture the global architecture of the semantic system, revealing how meanings are distributed, clustered, or integrated across the entire corpus.

In this section, we introduce measures within each of these three analytical levels, as summarized in Table 2, and discuss how they might be applied to both explicit usage and latent meaning semantic networks to capture different facets of meaning. Our aim is not to be exhaustive in translating all possible social network measures to the semantic domain. Instead, we identify measures that we believe show significant potential when applied in semantic network analysis, leaving further measurement adaptations to future research.

[INSERT TABLE 2]

Dyad-Level Measures

At the foundation of any semantic network is the dyad, which is the connection between two concepts. The key dyadic measure is the *existence of a tie*, which determines whether a relationship between two nodes is present. In network-analytic terms, this measure captures the most basic unit of relational meaning. Although conceptually simple, the dyad is critical because it specifies how meaning is instantiated, whether that is through direct linguistic linkage or inferred conceptual similarity.

In explicit usage networks, the existence of a tie reflects discursive co-occurrence, or whether two words are used together within a specified context window. As noted, the tie captures the observable association between concepts in communication. For instance, in letters to shareholders, the frequent co-occurrence between words like “innovation” and “growth” signals that these ideas are linguistically coupled in how speakers construct their narrative of success. The meaning of the tie is thus rhetorical in that it reveals which ideas are explicitly articulated together, co-framed, or treated as mutually relevant by the speaker in their communication.

In latent meaning networks, by contrast, the existence of a tie represents semantic similarity, or whether two words occupy nearby positions in a high-dimensional meaning space. Rather than tracking words that literally co-occur within the same sentence or document, latent ties reflect words that share similar contextual patterns across an entire corpus. For example, even if "innovation" and "uncertainty" rarely appear together, they may still be close in semantic space because they occur in similar linguistic environments, appearing for example alongside other terms such as "risk," "learning," or "creativity." This latent tie thus captures a deeper cognitive linkage, showing how actors conceptually relate different ideas even when they are not explicitly mentioned together.

Summary. Dyad-level measures serve as the building block of all subsequent measures, defining how the relationships between words are established and thus interpreted. In explicit networks, ties map the rhetorical architecture of language (i.e., how meanings are articulated together), while in latent networks, ties reveal the cognitive architecture of thought (i.e., how meanings are implicitly structured through shared associations). Both approaches yield insight into how language not only conveys ideas but also reflects the underlying organization of meaning.

Node-Level Measures

While dyadic ties form the building blocks of a semantic network, node-level measures reveal how individual concepts are positioned within the broader structure of meaning. These measures show not only which ideas are linked, but also which ones are broadly connected across the network or embedded within tightly clustered semantic neighborhoods. Node-level measures can be grouped into two broad families: *positional measures*, which capture a concept's role in the topology of connections, and *neighborhood structure measures*, which describe the embeddedness in its local semantic environment.

Positional Measures. Positional measures describe how centrally a word is situated in the network of meaning. The most straightforward is *degree centrality* (Freeman 1978), which counts how many ties a concept has and therefore identifies nodes that function as semantic hubs. In explicit usage networks, such concepts are rhetorically prominent, appearing frequently alongside many other terms (e.g., words like "financial" or "projection" in an earnings call). In latent meaning networks, high-degree concept is conceptually broad, connected to many regions of the semantic space (e.g., "platform," which is conceptually similar to "ecosystem," "orchestration," or "architecture".).

Eigenvector centrality captures influence based on the centrality of a concept's neighbors (Bonacich 1987). High-eigenvector concepts are connected to not just many others, but specifically to other well-connected concepts, making them anchors of meaning. In explicit usage networks, these are the symbolically dominant terms that shape the vocabulary of a field (e.g., words like "leadership" or "innovation" that co-occur with many other central terms). In latent meaning networks, they represent the cognitive anchors that organize the underlying meaning structure (e.g., core concepts like "capability," which is semantically connected with other central strategic terms).

In practice, degree centrality and eigenvector centrality often overlap. For example, "innovation" may simultaneously serve as a high-degree hub and an anchor of meaning in both explicit and latent semantic networks.

Neighborhood Structure Measures. While positional measures emphasize how a concept connects across the network, neighborhood structure measures focus on the internal organization of its immediate semantic neighborhood. *Ego density* is a key metric of assessing how tightly a node's neighbors are connected to one another, capturing embeddedness of a node in its local neighborhood (Hanneman and Riddle 2005). In explicit usage networks, high ego density indicates that a word tends to appear in a stable, well-defined topical cluster (e.g., "creativity" may consistently co-occur with "learning," "experimentation," and "failure," which also frequently co-occur with one another, forming a coherent discourse of innovation). In latent meaning networks, high ego density suggests that the underlying meanings associated with a word are closely related, reflecting a tightly bounded conceptual domain (e.g., "compliance" clustering tightly with "rules," "regulations," and "audit," reflecting a regulatory cognitive schema). Conversely, low ego density implies a more diffuse or contested meaning environment, where a concept is embedded within a tightly knit semantic neighborhood.

A second neighborhood-level property is *brokerage*, often captured by the inverse of Burt's (1992) constraint measure (e.g. Kwon et al., 2020; Quintane and Carnabuci, 2016; Zhang, Aven, and Kleinbaum, 2024). Whereas ego density focuses on the tightness of a node's neighbors, brokerage assesses how much those neighbors overlap in the structural opportunities they provide. Low brokerage means that a node's neighbors all "talk to the same others," limiting exposure to diverse meanings. High brokerage means that its neighbors are not well connected to one another, positioning the focal node at the intersection of otherwise separate regions of the network. In explicit usage networks, high brokerage reflects rhetorical boundary objects that allow speakers to integrate separate conversations (e.g., the term "sustainability" often connects distinct discussions of ethics and strategy). In latent meaning networks, high brokerage identifies cognitive recombinants or ambiguous concepts that can be used in distinct ways (e.g., the term "value" is used in context of financial performance as well as organizational ethics).

Summary. Node-level measures thus move beyond identifying which concepts are connected to uncover how they are positioned within the architecture of meaning. They reveal which ideas are most rhetorically visible, which serve as central anchors, how internally cohesive their surrounding semantic neighborhood are, and which concept link otherwise unconnected region of meaning. In doing so, these measures link the micro-level relationships among words to the meso-level organization of meaning that shapes how discourse and thought is structured.

Network-Level Measures

At the highest level of analysis, network-level measures capture the overall architecture of a semantic system, or how meaning is structured across an entire text corpus. These properties can be examined along two complementary dimensions: *network cohesion*, which assess the overall connectedness and of the network, and *network fragmentation*, which capture the degree to which the meanings cluster into coherent or distinct domains.

Network Cohesion. Network cohesion measures describe how connected and integrated the semantic meaning system is. The most fundamental network property is *density*, defined as the proportion of all possible ties that are present in the network (Wasserman and Faust 1994). In an explicit usage network, higher density indicates that communicators frequently link ideas together, producing rhetorically integrated or coherent discourse. In a latent meaning network, high density signals conceptual integration, meaning that ideas are cognitively aligned across the corpus, reflecting their shared understanding amongst actors. In both cases, low density suggests a more dispersed meaning structure.

Network Fragmentation. Fragmentation measures describe the degree to which the network breaks into subgroups or displays a community structure. One representative network measure is *modularity*, which assesses how the network divides into internally cohesive but externally distinct clusters (Newman 2006). In explicit usage networks, modularity identifies the extent to which there are discursive communities, or sets of words that tend to co-occur, forming distinct rhetorical frames or topics (e.g., "innovation and growth" vs. "ethics and responsibility"). In latent meaning networks, modularity uncovers the extent to which there are underlying schemas that structure collective cognition (e.g., "profit and efficiency" vs. "community and welfare" where economic and social logics do not overlap). Comparing modularity across corpora or over time can show whether meaning systems are consolidating into fewer, shared domains or splintering into multiple interpretive logics.

Summary. Network-level measures thus shift attention from individual concepts to the global architecture of meaning. By assessing the integration, differentiation, and cohesion of semantic systems, these measures reveal whether the explicit usage of communication or underlying latent shared cognition is unified or fragmented, stable or evolving, specialized or interconnected. Together, they enable comparative insights into how entire fields, organizations, or time periods differ in the way they construct and organize meaning.

PRACTICAL APPLICATIONS

To illustrate the utility of our framework, we present two practical applications situated within the context of firms' quarterly earnings calls. As a prominent setting in organizational scholarship, earnings calls offer a window into how executives conceptualize and communicate strategic issues. Leveraging a corpus of earnings transcripts from all U.S. public companies over the past five years (see Appendix A), our aim is not to present a full empirical test, but rather, to demonstrate how SemNA can be used to investigate two topics of organizational interest: 1) the rapidly changing meaning of artificial intelligence and 2) the implicit gender bias within executive communication.

Application #1: The Changing Meaning of "Artificial Intelligence"

One of the most salient issues in today's business environment is artificial intelligence (AI). Far from being merely a technical upgrade, AI is fundamentally reshaping organizational reality, altering daily workflows, redefining strategic advantage, and disrupting industry boundaries. However, the meaning of "AI" within organizations is not static; rather, the concept has undergone a rapid transformation over the last five years. As the technology evolved from predictive analytics to generative capabilities, the language executives use to describe its value, risks, and applications has also ostensibly shifted. This evolution is critical, as the way organizations define AI shapes how they ultimately utilize it. This prompts our first question: *How might we use SemNA to capture the evolution of how organizations characterize and understand AI?*

To answer this, we construct an explicit usage semantic network. As our framework explains (see Table 1), explicit networks are ideal for studying phenomena where meaning is emergent or actively being constructed through communication. Given that organizations are currently making sense of these technologies and signaling adoption to stakeholders, mapping observable co-occurrences allows us to trace exactly how the rhetorical framing of AI has shifted over time. We compare quarterly earnings calls from 2021 with those from 2024, which bookends the widespread commercial introduction of generative AI. We define our nodes using an expansive dictionary of AI-related terms (e.g., "LLM," "personalization," "ethics") and define ties based on sentence-level co-occurrence (see Appendix B).

We begin at the dyadic level—or the *existence of a tie*—to investigate which concepts organizations explicitly link with "AI." Figure 2 compares the explicit usage networks from 2021 and 2024. In 2021, executives invoked "AI" in broad, aspirational terms. The concept frequently co-occurred with abstract descriptors such as "innovation," "efficiency," and "automation," suggesting that while firms recognized AI's potential, the discourse treated the technology as a generic driver of future performance rather than a specific operational tool. By 2024, the network structure shifted markedly. The concepts co-occurring with "AI" became far more technical and increasingly focused on governance. Co-mentions with terms like "generative," "LLM," and "retrieval" became common, reflecting growing organizational fluency with underlying architectures. Moreover, organizations began coupling "AI" with "ethics," "responsibility," and "privacy," signaling heightened attention to regulatory obligations.

[INSERT FIGURE 2]

We can also examine node-level measures to reveal how the structural positions of key concepts have changed. First, changes in *degree centrality* highlight the rising visibility of infrastructure- and governance-related concepts. Technical terms that were relatively peripheral in 2021 became substantially more central in 2024. For example, the term "GPU" rose in prominence, with its degree centrality increasing from 0.043 in 2021 to 0.186 in 2024. Governance-oriented terms followed a similar trajectory. The term "sovereignty" increased in centrality from 0.012 in 2021 to 0.023 in 2024, reflecting increasing concern about data control and geopolitical constraints. Second, changes in *brokerage*, captured by structural constraint, reveal how concepts evolved to bridge distinct conversations. For instance, Figure 3 shows how the term "generative" exhibited relatively high constraint in 2021 (0.211), but substantially lower constraint in 2024 (0.029). This shift reflects a change from being exclusively part of a local cluster in 2021, often associated only with financial terms like "cash-generative," to being in a high-brokerage position in 2024, operating as a bridge between different conversations involving technical terminology and monetization strategies (see Figure 3).

[INSERT FIGURE 3]

Finally, we examine network-level measures to understand the global architecture of this semantic evolution. Consistent with the trends observed at the dyadic and node levels, the overall semantic network surrounding AI became more cohesive and integrated over time. Specifically, *network density* increased from 0.229 in 2021 to 0.241 in 2024, indicating that a larger share of possible conceptual linkages is now realized in organizational communication. Rather than being discussed in isolated or fragmented pockets, AI-related concepts are increasingly synthesized into a more integrated and coherent narrative.

Taken together, these results illustrate the rapid discursive maturation of AI. By employing SemNA, we move beyond simply noting that AI is "popular" to mapping the precise structural transformation of its meaning. For example, whereas dictionary-based approaches capture changes in term frequency and topic models infer latent thematic mixtures, explicit usage semantic networks preserve the observable relationships among individual concepts. This structural perspective allows us to examine how key AI-related concepts are embedded in the topology of meaning enacted in these texts as well as how these relationships evolve over time. In doing so, we uncover a clear trajectory where the vague, aspirational rhetoric of 2021 has crystallized into a concrete discourse defined by technical precision and institutional responsibility, with certain concepts increasingly bridging distinct domains.

Application #2: Implicit Gender Bias

A second relevant topic in organizational scholarship is the persistence of gender bias. Despite significant efforts to promote diversity, bias often remains embedded in the deep structures of organizational life, operating less through overt discrimination and more through implicit cognitive schemas. These schemas shape how we categorize and evaluate others, frequently associating men with agency and leadership while relegating women to communal or support roles. However, measuring these biases is notoriously difficult because they are rarely articulated explicitly. Indeed, executives do not openly state that they view female leaders differently than their male counterparts. Instead, these biases exist as subtle, taken-for-granted associations that structure cognition. This leads to our second question: *How might we use SemNA to uncover the implicit gender biases in executive communication?*

To explore this, we construct a latent meaning semantic network. As our framework explains (see Table 1), latent networks are uniquely suited for capturing the underlying structure of meaning, or the sedimented associations that actors rarely make explicit but that nevertheless shape their thinking. We analyze 2024 earnings call transcripts, training a Word2Vec embedding model to generate high-dimensional vector representations for the corpus. In this network, nodes represent semantic concepts defined by their vector positions, while ties represent the cosine similarity between them (see Appendix C). Crucially, while standard word embedding approaches stop at calculating the distance between words, transforming these vectors into a network allows us to analyze the topology of the semantic space itself.

We once again begin with a dyadic measure—the *existence of a tie*—to investigate specific concepts associated with gendered pronouns. Consistent with prevailing assumptions on gender stereotyping, we find sharp differences in the semantic contexts surrounding female versus male pronouns. As shown in Figure 4, female pronouns ("she," "her") exhibit their strongest similarities to family-role concepts, such as "wife" and "daughter." By contrast, male pronouns ("he," "his") align closely with professional-role concepts, including "successor," "colleague," and "career." These dyadic similarities confirm that within the cognitive schema of corporate leadership, women are implicitly situated in relational terms, whereas men are positioned as autonomous professional actors.

[INSERT FIGURE 4]

These patterns become even clearer—and methodologically distinct—when we shift to node-level measures to reveal the structural organization of these semantic neighborhoods. First, we examine local cohesion using the *ego density* measure. Female pronouns exhibit substantially higher ego density on average (0.583) compared to male pronouns (0.357). This indicates that the words surrounding "she" and "her" are not only associated with the pronoun but are also highly interconnected with one another. This offers a critical structural insight that standard embeddings would obscure. While a standard embedding model identify which words are similar to "she" (producing a ranked list of nearest neighbors), it ignores the relationships between those neighbors. By measuring density, SemNA reveals that the female semantic space is a tight knit, self-reinforcing pocket where concepts lock together to form a singular, monolithic identity. In contrast, the lower density around male pronouns suggests a more fragmented and flexible semantic structure. This implies that in the corporate cognitive schema, "men" are permitted to inhabit multiple, disconnected roles simultaneously (e.g., being a "father" does not semantically crowd out being a "CEO"), whereas "women" are confined to a rigid category where domestic and communal attributes structurally collapse into one another, leaving little room for semantic nuance or multidimensionality.

Second, we examine *brokerage* using the measure of structural constraint. Female pronouns show substantially higher constraint (0.537) compared to male pronouns (0.326), indicating that their semantic neighbors are largely redundant (i.e., connected to the same concepts and offering little access to diverse meaning regions). This again reveals methodological novelty of SemNA. While a vector-based approach can identify that "he" is semantically close to "strategy" and "operations," it does not offer a measure of whether "he" links concepts within the same semantic domain or bridges across distinct domains. By calculating brokerage, SemNA exposes that male pronouns act as semantic bridges, filling structural holes between distinct organizational domains (e.g., linking technical expertise with executive leadership). In contrast, the high constraint or low brokerage position surrounding female pronouns implies a structural trap. In other words, the semantic space around them is closed and self-referential, limiting the ability of female executives to be perceived as multifaceted leaders who can span boundaries.

Taken together, these results reveal that implicit gender bias is embedded in corporate discourse, even when gender is never an explicit topic of conversation. This bias appears not only in the specific concepts associated with pronouns but in the structural positions those pronouns occupy. This application illustrates how latent meaning networks address the displacement issue by doing what embeddings alone cannot—that is, visualizing and measuring the topological constraints that cognitive schemas impose on organizational actors.

GENERAL DISCUSSION

This paper advances a conceptual framework for applying SemNA in organizational research. By distinguishing between explicit usage and latent meaning networks and adapting established social network measures to capture local and global structures of semantic meaning, we offer a systematic approach for using SemNA to model and interpret the architecture of meaning in text. In the discussion that follows, we consider the broader implications of this framework. We first highlight potential theoretical applications to illustrate how SemNA might enrich theory and empirical research in a variety of literatures broadly interested in communication and cognition. We then outline the method's key limitations and conclude by identifying directions for future research that could further extend both the theoretical and computational use of SemNA in organizational analysis.

Advancing Organizational Scholarship

In this section, we discuss how our framework might enrich organizational research across a variety of scholarly conversations. Table 3 outlines these conversations, pairing them with different types of research questions that would suggest the use of either an explicit usage or latent meaning semantic network. To organize these literatures, we break our discussion into 1) *organizational activities*, which focus on internal dynamics such as strategy-making and culture, and 2) *market and institutional activities*, which examine broader field-level phenomena such as categorization and legitimation. Our aim in this section is not to be exhaustive, but suggestive and generative in the types of insights SemNA might open up across different conversations.

[INSERT TABLE 3]

Organizational Activities

Scholars interested in the internal activities of organizations—such as leadership, sensemaking, teams, and culture—share an interest in how meaning is constructed, shared, and utilized to accomplish goals. Whether examining how a leader motivates employees or how a team coordinates complex tasks, these literatures often explore two different types of meaning: it is both a resource that actors actively mobilize through communication and a structure that exists as a cognitive backdrop. We believe that distinguishing between explicit usage and latent meaning networks allows researchers to empirically capture both sides.

Scholars can utilize *explicit usage semantic networks* to explore how actors strategically mobilize language to achieve specific outcomes. In the domain of leadership, for example, researchers often rely on content analysis or word counts to identify effective communication strategies (e.g., Elsbach 1994, Rhee and Fiss 2014). SemNA complements these approaches by offering insight into the structural organization of communication. Rather than focusing solely on isolated terms leaders use, researchers can examine how leaders bridge different types of ideas, such as linking abstract strategic goals to concrete daily operations, or future-oriented terms to the existing vocabulary of the organization (e.g., Carton et al. 2014). Explicit networks might also offer a new way to trace the evolution of organizational culture. When new members enter an organization, researchers can move beyond simply assessing whether newcomers adopt the dominant jargon to examining how the organization's semantic structure itself shifts. This perspective allows scholars to assess whether new entrants introduce novel structural connections or are rhetorically assimilated into the existing network of meaning (e.g., Greenwood and Hinings 1996, Zilber 2002). Furthermore, this approach might also be used to study how teams develop a distinct shared vocabulary to coordinate daily tasks (e.g., Okhuysen and Bechky 2009, Valentine 2018), measuring not just the overlap in words but the emergence of words that come to occupy bridging positions within a semantic network, thereby facilitating coordination efficiency across different groups.

In contrast, *latent meaning semantic networks* generate insights into the implicit, taken-for-granted cognitive structures that constrain action. At the team level, this approach could offer a novel way to operationalize how shared mental models among team members is structured. Existing approaches often focus on identifying dominant words or jargons in team communication, typically by examining the frequency with which particular terms are used (DeChurch and Mesmer-Magnus 2010)). Latent meaning semantic networks could complement this work by enabling researchers to investigate the topology of team mental models, identifying which concepts occupy central positions in the team's implicit understanding and which concepts serve as bridges between otherwise distinct interpretations held by different members. Moving to the organizational level, latent networks also offer a powerful way to operationalize organizational culture and dominant logic. Rather than treating culture as a general "climate," SemNA allows scholars to measure it as the rigidity of the semantic network. A strong culture may be characterized by high network density, where meanings are tightly interlocked and resistant to reinterpretation. This structural view provides a precise mechanism for understanding why incumbents might struggle to adapt to change, in that it is not just that they "miss" new information, but that their sedimented cognitive structures are too topologically rigid to accommodate new conceptual connections (Gavetti et al. 2007, Kaplan and Tripsas 2008).

Taken together, SemNA has the potential to contribute to these conversations by shifting the analytical focus from the inventory of the words being used to the visual mapping of how meanings are organized. By creating structural representations of both communication and cognition, our framework allows scholars to empirically capture complex "meaning systems" and employ rigorous network measures to explain how those systems facilitate coordination or constrain adaptation.

Market and Institutional Activities

Scholars interested in the external activities of organizations—spanning categories, cultural entrepreneurship, and institutions—examine how markets are constructed, how legitimacy is acquired, and how fields evolve. Whether examining how an entrepreneur shapes a new market or how actors disrupt established institutions, these literatures are similarly interested two types of meaning: it is both a strategic tool for shaping the environment and a sedimented reality that defines the boundaries of legitimate action. We believe that applying the distinction between explicit usage and latent meaning networks allows researchers to rigorously model this interplay between agency and structure.

Scholars can utilize *explicit usage semantic networks* to explore how actors strategically mobilize language to reshape market boundaries. In the literature on cultural entrepreneurship, for example, success often hinges on achieving “optimal distinctiveness” by balancing novelty and familiarity. SemNA could allow researchers to identify concepts that bridge a dense cluster of familiar terms and a novel domain, which actors can deploy strategically through analogies or metaphors (e.g., Lounsbury and Glynn 2001, Zott and Huy 2007, Harmon et al. 2023). Similarly, in the study of category emergence, explicit networks can map how category and market boundaries are actively constructed and contested (e.g., Kennedy 2008). As described in our practical application, the structural shift of key terminologies related to AI highlights how people’s understanding and discourse around the concept have changed over time. This approach also offers a promising lens for institutional work by allowing scholars to visualize the “discursive scaffolding” actors build to defend the status quo, such as how they strategically increase the semantic density around core values to ward off external challenges (Lawrence and Suddaby 2006).

In contrast, *latent meaning semantic networks* reveal the underlying, sedimented structures of a field that determine the boundaries of legitimacy. For category scholars, this offers a method for measuring category spanning and distinctiveness. Current methods often rely on overlap in feature lists. SemNA, however, allows researchers to measure the core-periphery structure of a category. A “crisp” category is not just one with unique words, but one with a highly dense latent core; conversely, a “fuzzy” category exhibits a diffuse topology. This could allow scholars to measure the mechanism of the “penalty” for spanning by calculating the shortest distance an organization must traverse to bridge two distinct categorical cores (e.g., Hsu 2006, Hsu et al. 2009). Moving to the level of institutional logics, latent networks provide a new way to map the structural polarity of a field by measuring whether meaning is topologically fragmented into distinct, non-communicating clusters. Once this structure is identified, scholars can then assess the extent to which individual actors align with these clusters. This enables a distinction between surface-level rhetorical compliance and deep structural adherence, in which an actor’s underlying semantic patterns genuinely align with the logic’s meaning system (e.g., Thornton et al. 2012, Glaser et al. 2016).

In summary, SemNA provides a granular analysis of market and institutional activities that distinguishes between the strategic enactment of fields and their underlying architecture. We believe this framework has the potential to advance these scholarly conversations by moving beyond the measurement of field “states” (e.g., is this category legitimate?) to the measurement of field “topology” (e.g., how porous are its boundaries?). By creating structural representations of both strategic action and institutional constraint, SemNA allows scholars to empirically capture the dynamic interplay of agency and structure, opening new avenues for research on how fields evolve, fracture, and settle.

Limitations of SemNA

Like all NLP methods, SemNA comes with important methodological constraints. No representation of text is perfect, and each approach—whether dictionaries, topic models, word embeddings, or SemNA—captures some aspects of meaning while inevitably flattening others (Hannigan et al. 2019, Aceves and Evans 2024). Understanding these boundary conditions is essential for interpreting findings responsibly. SemNA offers a powerful way to visualize and quantify relationships among concepts, but the insights it generates depend on how the network is constructed, how semantic information is simplified, and how well the method scales with corpus size. In this section, we outline these limitations and explain how they can affect the use of SemNA.

A first limitation concerns the method’s sensitivity to analytic design choices. Semantic networks do not naturally emerge from text but instead are built through a series of researcher decisions, such as how to define co-occurrences or semantic similarity, which thresholds to use when determining ties, how to delimit the corpus, and which embedding model or context window to adopt. Small changes in these parameters can meaningfully alter network structure, shifting which concepts appear central, which clusters form, and what theoretical patterns seem to "exist" in the data. As a result, substantive findings may reflect modeling assumptions as much as underlying meaning. When considering this issue, researchers should explicitly justify their design decisions, assess the robustness of results across alternative specifications, and validate networks with domain expertise or complementary qualitative evidence.

A second limitation is the loss of semantic information inherent in translating rich, context-dependent language into a simplified network of nodes and edges. Language is high-dimensional and syntactically structured, with meaning emerging from word order, composition, and context. SemNA necessarily compresses this complexity by reducing multi-dimensional meaning to a lower-dimensional network structure. Of course, this reduction is also the method's primary strength. Indeed, by stripping away some complexity, SemNA renders the unmanageable vastness of language into a tractable structure, allowing scholars visualize and analyze both the local and global architecture of meaning. At the same time, SemNA should be understood as analytic abstractions rather than literal reflections of all nuances of linguistic interpretations. Individual ties are therefore best interpreted cautiously and in relation to broader network patterns in the global network, and researchers should even consider supplementing SemNA with other methods to enhance and triangulate interpretation.

A third limitation involves scalability and density. As corpora grow larger, semantic networks tend to become extremely dense because many words co-occur or exhibit high similarity in large text collections. Dense networks can become visually cluttered, computationally cumbersome to analyze, and theoretically uninformative as everything becomes connected. In these settings, global network measures can lose interpretive power and patterns that seemed meaningful at smaller scales can dissipate into noise. To mitigate these challenges, researchers might consider using stricter tie thresholds, pruning weak or trivial connections, or sampling and stratifying large corpora before constructing networks. Focusing on cluster-level or node-level patterns—rather than attempting to interpret the entire global structure—can also help preserve meaningful signal.

Future Extensions

This paper has developed a conceptual framework that clarifies how SemNA can be constructed and used in organizational scholarship. Our goal has been to provide a starting point rather than a definitive set of procedures. At the same time, there are also variations and extensions of this starting point that offer promising avenues for future work. We discuss four possibilities below.

One extension concerns the level of semantic granularity used when constructing networks. Although words often serve as the basic unit of analysis, researchers may wish to consider nodes that represent sentences, paragraphs, full documents, or symbolic expressions such as tags or formulas. Adjusting granularity in this way enables scholars to capture meaning at the level where actors construct arguments, frame issues, and make sense of their environment. It also allows semantic network analysis to accommodate the multimodal forms of communication that characterize contemporary organizational life. In doing so, researchers can more fully model how meaning is structured in practice and how actors rely on different expressive forms to convey ideas.

A second extension involves examining the temporal relationships and dynamics within and between semantic networks, with particular attention to the interplay between explicit usage and latent structures of meaning. Meaning is continually shaped through repeated communication, and future work might model how these dynamics unfold over time. This temporal orientation makes it possible to observe when explicit word pairings gradually reshape deeper patterns of semantic association and when repeated usage fails to shift underlying meaning structures. It also allows scholars to identify moments when explicit discourse and latent meaning move in different directions, revealing sites of tension, drift, or semantic innovation. Studying this interplay offers new insight into processes such as the escalation of crises, the stabilization of new frames, and the gradual transformation of institutional logics.

A third extension centers on linking semantic networks with cognitive and social networks. Meaning is not only embedded in language but also shaped by the mental associations that individuals hold and the social relationships through which these associations circulate. Integrating semantic structures with social structures would enable scholars to explore how interpretive resources are distributed across groups, how social position influences access to and use of particular meanings, and how collective sensemaking processes emerge from patterns of interaction. This integration provides an opportunity to connect micro-level cognition, meso-level relationships, and macro-level systems of meaning within a single analytic approach.

A final extension involves combining semantic network analysis with other NLP methods. While latent meaning networks already draw on embedding models, researchers might incorporate additional tools such as topic modeling, dependency parsing, sentiment and emotion analysis, named entity recognition, and contextual embedding models. For example, a study of earnings call communication might begin by extracting named entities to identify which firms, products, or executives appear in the discourse, apply dependency parsing to capture how these entities are described or related, and then integrate sentiment analysis to assess the emotional tone surrounding particular concepts. When mapped into a semantic network, these layers would reveal not only how ideas are connected but also how they are framed, evaluated, and distributed across actors. Integrating such methods allows scholars to construct more comprehensive representations of meaning and to better interpret the complex linguistic patterns that characterize organizational communication.

Conclusion

SemNA provides a systematic way to examine how meaning is organized and expressed in text, and we believe it holds substantial promise for revitalizing the structural analysis of text in organizational research. By distinguishing between explicit usage and latent meaning, our framework allows scholars to capture the dual nature of meaning as both a communicative resource that actors actively mobilize and a cognitive structure that constrains them. In doing so, SemNA encourages researchers to move beyond the simplicity of frequency counts and the opacity of high-dimensional vectors, offering instead a method that is both mathematically rigorous and theoretically interpretable. As textual data becomes increasingly central to organizational inquiry, we hope this framework inspires scholars to look past the mere presence of words to investigate the architecture of the meanings that shape organizational life.

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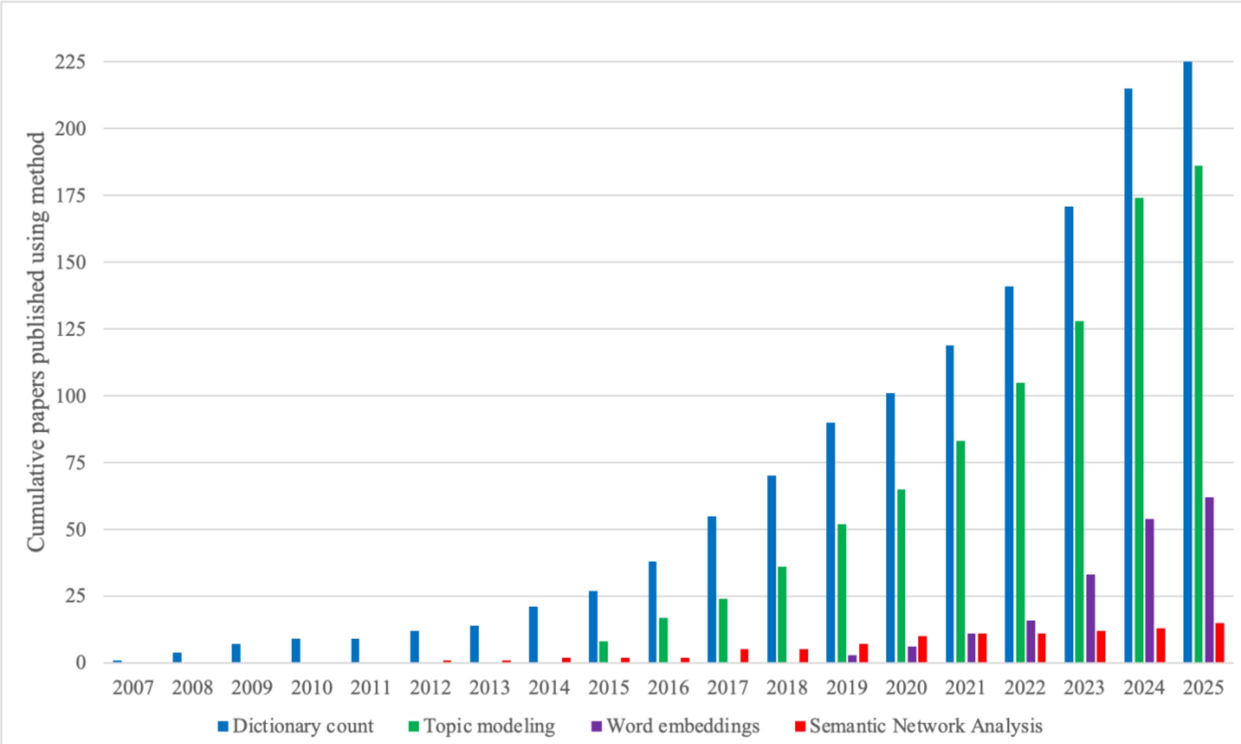
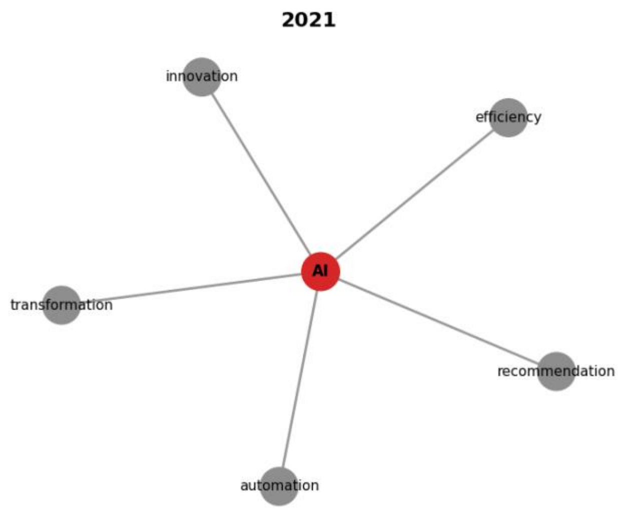
Figure 1. Papers published in organization science using NLP methods*



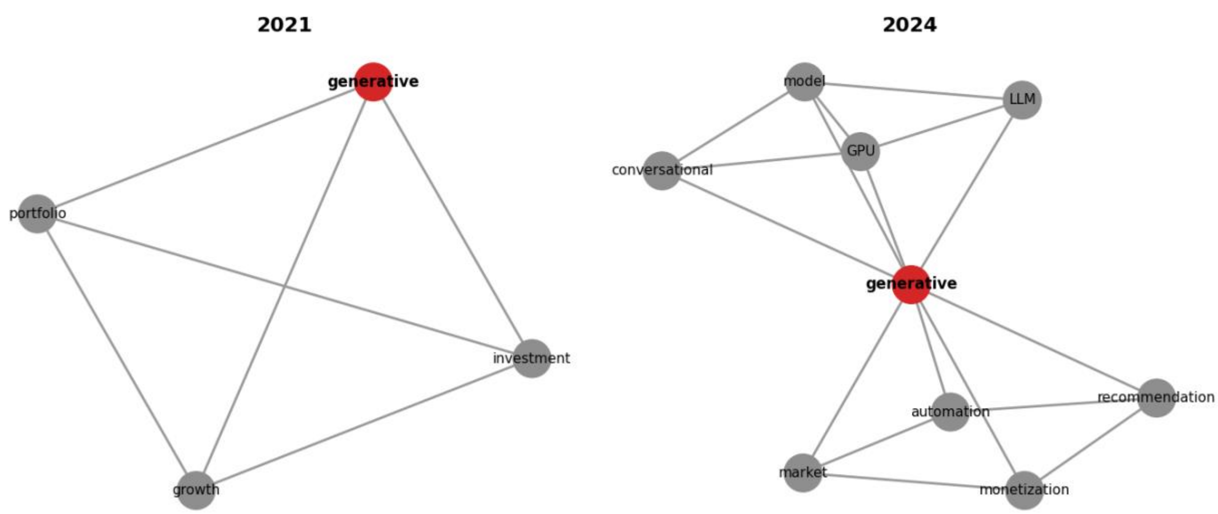
* Published in *Academy of Management Journal*, *Administrative Science Quarterly*, *Journal of Applied Psychology*, *Journal of Management*, *Organizational Behavior and Human Decision Processes*, *Organization Science*, *Organization Studies*, *Management Science*, and *Strategic Management Journal*.

Figure 2. Semantic neighborhood "AI" in explicit usage network



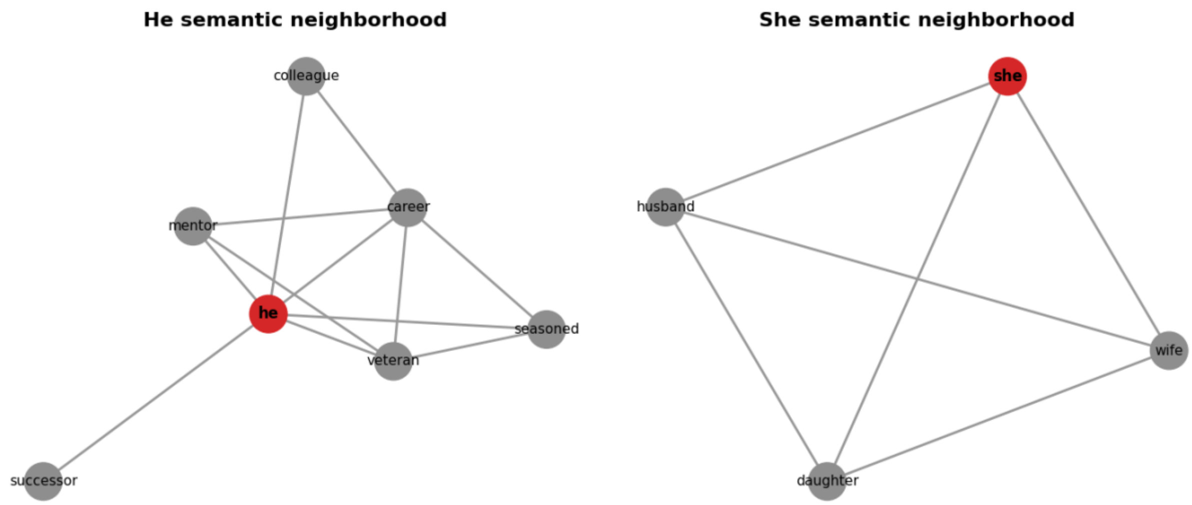
Nodes displayed represent a selective set of semantic concepts from the explicit usage semantic network in the designated year. The 2024 panel highlights semantic concepts that emerged or become especially salient in the semantic network relative to 2021. Ties represent that co-occurrences between the two words exceeded a predefined threshold (see Appendix B).

Figure 3. Ego network of "generative" in explicit usage network



Nodes displayed represent a selective set of semantic concepts from the explicit usage semantic network in the designated year. The 2024 panel highlights semantic concepts that emerged or become especially salient in the semantic network relative to 2021. Ties represent that co-occurrences between the two words exceeded a predefined threshold (see Appendix B).

Figure 4. Ego network of "he" and "she" in latent meaning semantic network



Nodes displayed represent selective set of semantic concepts from the latent meaning semantic network for the "he" and "she" ego networks. Ties represent that the cosine similarity between the two words exceeded a predefined threshold (see Appendix C).

Table 1. Two Types of Semantic Networks

	Explicit Usage Semantic Network	Latent Meaning Semantic Network
Network Interpretation		
Overall network	Explicit semantic relationships in text.	Latent semantic relationships in text.
Tie	Inferred by the researcher based on what they believe co-occurrence represents in that context.	Semantic similarity between concepts.
Cluster of nodes	Concepts that are explicitly talked about together	Concepts that fit together in extant knowledge.
Dimensionality	One-dimensional	Multi-dimensional
Observability	High; researcher can easily observe concepts explicitly used together in text.	Low; researcher may not observe the relationships between concepts in text.
Use Cases		
Theory-related	When studying meanings explicitly enacted by actors (e.g., individuals, firms, etc.).	When studying latent meanings not observable in spoken language.
Data-related	When dataset has sufficient frequency of terms to estimate meaningful co-occurrence statistics.	When dataset is large and when concepts are used in semantically different ways.
Phenomena-related	When trying to capture meanings that are emergent, changing, or being contested.	When trying to capture latent meanings that remain relatively stable within training corpus.
Examples		
Key citations	Kennedy (2008): co-occurrence of firm names in media to study the emergence of market category. Giorgi et al. (2019): co-occurrence between "safety" and related terms to study changes in meaning in the automotive industry. Godart & Galunic (2019): co-occurrences between stylistic elements mentioned by fashion houses to study popularity over time.	Veremyev et al. (2019): embedding-based networks to map latent meaning similarity. Song & Harmon (2025): semantic similarity networks of discourse around novel ideas.

Table 2. Measuring Semantic Networks

Level of Analysis	Measure	Definition	Reference	Interpretation
Dyad	**Existence of Tie**	Indicates whether two nodes are connected, forming the basic link in the network.	Wasserman & Faust (1994)	Explicit: represents discursive co-occurrence—words that appear together in text, revealing how ideas are linguistically coupled. Latent: represents semantic similarity—words with comparable contextual embeddings, revealing shared underlying meaning.
Node	**Degree Centrality**	Number or total weight of ties incident on a node.	Freeman (1978)	Explicit: indicates rhetorical visibility—how broadly a concept is used with others in discourse. Latent: indicates conceptual generality—how broadly a concept relates to others in shared meaning space.
	Eigenvector Centrality	Influence of a node based on ties to other highly connected nodes.	Bonacich (1987)	Explicit: identifies symbolically dominant language used alongside other central terms. Latent: signals core conceptual anchors structuring collective meaning.
	Ego Density	Proportion of realized ties among a node's immediate neighbors.	Hanneman & Riddle (2005)	Explicit: captures local rhetorical coherence—how interrelated the immediate linguistic context of a word is. Latent: captures local conceptual cohesion—how unified a concept's surrounding meanings are.
	Brokerage	Extent to which a node links otherwise disconnected clusters, creating interpretive bridges.	Burt (1992)	Explicit: highlights framing devices that integrate separate discourses or audiences. Latent: reveals conceptually ambiguous ideas that can be understood from different perspectives.

Network	**Density**	Proportion of all possible ties that are present in the network.	Wasserman & Faust (1994)	Explicit: measures rhetorical integration—how interlinked the language of a corpus is. Latent: measures cognitive integration—coherence of the underlying meaning system.
	Modularity	Extent to which nodes form internally cohesive clusters with few external ties.	Newman (2006)	Explicit: reveals the extent to which there are discursive communities or topical clusters in language use. Latent: reveals the extent to which there are conceptual domains or meaning systems underlying cognition.

Table 3. Using SemNA to Advance Organizational Scholarship

Level of Analysis	**Explicit Usage Semantic Network** (Enacting Meaning)	**Latent Meaning Semantic Network** (Underlying Meaning Structures)
Organizational Activities		
Leader Communication	*How do leaders motivate employees or influence external stakeholders?* (Elsbach 1994, Carton et al. 2014, Rhee and Fiss 2014, Stam et al. 2014)	*What are the implicit biases or stereotypes that leaders convey in their communications?* (Heilman and Haynes 2005, Ziegert and Hanges 2005, Lyness and Heilman 2006)
Sensemaking & Crises	*How do actors give sense to or construct a coherent narrative during a crisis?* (Fiss and Zajac 2006, Maitlis and Christianson 2014, Bundy et al. 2017)	*What is the underlying structure of reality during a crisis, and does it resist change in the face of external shocks?* (Weick 1993, Weick et al. 2005, Harmon 2019)
Teams & Groups	*How do teams actively coordinate and develop a shared vocabulary to manage daily tasks and conflict?* (Okhuysen and Bechky 2009, Valentine 2018)	*To what extent do teams share a deep, implicit structure of tasks or knowledge?* (Mathieu et al. 2000, Lewis 2003, DeChurch and Mesmer-Magnus 2010)
Organizational Attention & Cognition	*How is organizational attention explicitly directed toward specific issues during decision-making?* (Ocasio 1997, Rhee and Leonardi 2018)	*What are the sedimented cognitive structures or dominant logics that filter information and constrain search?* (Walsh 1995, Gavetti et al. 2007, Kaplan and Tripsas 2008)
Organizational Culture	*How does an organization's culture change over time?* (Greenwood and Hinings 1996, Rousseau and Tijoriwala 1999, Zilber 2002)	*What are the deep cultural codes that persist beneath the surface of an organization's culture?* (Goldberg 2011, Srivastava and Goldberg 2017, Corritore et al. 2020)
Market and Institutional Activities		
Categories	*How do new categories emerge or how do actors use categories strategically?* (Kennedy 2008, Durand et al. 2017, Granqvist and Siltaoja 2020)	*What are the features of a given market category, and how do they overlap with other market categories?* (Lounsbury and Rao 2004, Hsu 2006, Hsu et al. 2009, Zunino et al. 2019)
Cultural Entrepreneurship	*How do entrepreneurs construct or shape new markets?* (Lounsbury and Glynn 2001, Zott and Huy 2007, Harmon et al. 2023)	*What are the latent cognitive landscapes entrepreneurs can draw upon as a stock of knowledge to gain legitimacy?* (Lounsbury and Glynn 2019, Song and Harmon 2025)
Institutions	*How do actors use rhetorical strategies to create, disrupt, or maintain institutions?* (Suddaby and Greenwood 2005, Lawrence and Suddaby 2006)	*What are the deep, sedimented belief systems and cultural codes that structure a field?* (Thornton et al. 2012, Jones et al. 2012, Glaser et al. 2016, Jancsary et al. 2017)

APPENDIX

Appendix A. Earnings call data construction and text cleaning

Our sample includes all publicly available earnings call transcripts from U.S. firms from Q1 2021 to Q3 2025, obtained through the Financial Modeling Prep (FMP) API. For Application #1, which examines the changing meaning of AI, we focus transcripts from 2021 and 2024, the most recent full-year sample available. For Application #2, which investigates implicit gender bias, for simplicity we use the 2024 dataset only. The 2024 corpus contains transcripts for 3,195 companies across four quarters, providing substantial variation in linguistic style, topical content, and firm context.

Each earnings call includes both a prepared presentation, where executives deliver scripted remarks, and a Q&A session, where analysts' questions often prompt unscripted responses. For text preprocessing, we first removed special characters, stop words, and numbers. We then transformed the cleaned text into a bag-of-words representation and lemmatized each token. This resulted in a total of 4,633,208 sentences accounting for 47,465,885 words.

Appendix B. Node and edge selection criteria for explicit usage network

To examine the changing meaning of artificial intelligence using the explicit usage network, we defined nodes as a set of terms relevant to artificial intelligence (AI) as it appears in managerial discourse. Instead of relying on a broad dictionary or including all words that happen to co-occur with "AI," we compiled a conceptually grounded list of 215 AI-relevant keywords to ensure that the explicit usage pattern is not masked by co-occurrences among an overly broad collection of loosely related terms. This list spans several topical domains central to contemporary AI discussions in the past five years, including business applications such as "personalization" and "recommendation," governance-related concepts such as "ethics" and "compliance," and core technological terms such as "multimodal" and "encryption."

Edges in the explicit usage network are formed based on sentence-level co-mentions. That is, two AI-related terms are considered connected if they appear together within the same sentence. We determine the co-occurrence threshold using the t-score, a statistical measure that assesses whether the level of co-occurrence between the two terms is above the one that would be expected by chance given their individual frequencies. Examining the distribution of t-scores across all possible word pairs, we found that the top five percent corresponded to a value of approximately 2.5, which indicates a substantively meaningful association rather than random co-usage. We therefore adopted t-score ≥ 2.5 as our criterion for establishing edges in the explicit usage network.

To ensure the validity of this threshold, we evaluated several global properties of networks constructed at adjacent cutoffs. Specifically, we compared network density, the number of connected components, and modularity at values near 2.5. These structural features remained largely stable across nearby thresholds, indicating that the network does not undergo discontinuous shifts at 2.5. We also found that the conceptual patterns and examples used in the Practical Application section remained consistent under alternative thresholds. Together, these checks provide confidence that the insights drawn from the explicit usage network are not sensitive to the threshold used.

Appendix C. Node and edge selection criteria for latent semantic network

To identify the implicit meaning structures embedded in executive communication, we constructed a latent semantic network using the full corpus of 2024 earnings call transcripts. We began by training a Word2Vec embedding model (Kozlowski et al. 2019, Lix et al. 2022) on the fully preprocessed 2024 corpus. We set the vector dimensionality to 300 to minimize the error of the word-context matrix and provide a sufficiently rich semantic space (Mikolov, Sutskever, et al. 2013). Rare words under the minimum occurrence threshold of 20 in the sample are excluded when training the word embedding model to ensure stable vector estimates. This procedure generates a high-dimensional vector representation for each word, placing semantically similar terms closer together based on the contexts in which they appear throughout the earnings calls. Such vector representation of words retained in the embedding model represent nodes in the latent semantic network.

Ties in the latent semantic network are defined based on cosine similarity between word vectors. Cosine similarity captures the degree to which two words are contextually similar, making it an established measure of latent semantic association (Mikolov, Yih, et al. 2013, Mikolov, Chen, et al. 2013, Kozlowski et al. 2019, Vossen and Ihl 2020, Lix et al. 2022). We use a cosine similarity threshold of 0.60 to designate the presence of a tie. This level reflects a substantively meaningful degree of semantic overlap, as confirmed through several validated in-sample examples. To assess the robustness of this threshold, we examined global network properties—such as density, number of components, and modularity—across adjacent similarity cutoffs. These properties remained stable across nearby thresholds, indicating that the network does not undergo structural discontinuities at 0.60. We also verified that the illustrative examples used in the implicit gender bias application yielded similar patterns under higher or lower thresholds. Together, these checks provide confidence that the findings are not sensitive to the cosine similarity threshold used.

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