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Probabilistic Semantic Betweenness Centrality in Cognitive Networks

Dmytro Lande[1], Anatolii Kachynskyi[1], Oleksii Novikov[1] and Leonard Strashnoy[2]

[1] National Technical University of Ukraine "Igor Sikorsky Kyiv Polytechnic Institute," Educational and Scientific Physical-Technical Institute
[2]University of California (UCLA), Los Angeles, USA

Abstract. This paper proposes a novel approach to analyzing node centrality in information networks, based on the semantic diversity of paths. It is shown that traditional metrics, such as betweenness centrality, are limited by topological logic: they account only for the number of shortest paths, ignoring their semantic content. In social and cognitive networks, paths possess semantic properties, such as resilience to countermeasures, scale of impact, resource intensity, or legitimacy. The paper examines the concept of semantic betweenness centrality (SBC) as a distinct metric for each semantic optimality criterion. To overcome the limitations of the deterministic approach, an extended model is proposed: Probabilistic Semantic Betweenness Centrality (PSBC). This model integrates a logical-probabilistic approach, evaluating centrality proportionally to the probability of realizing a specific semantic path. This allows for filtering out "theoretically optimal" but improbable chains of influence, focusing instead on genuinely threatening or highly effective trajectories. Using the example of a cognitive warfare semantic network, it is demonstrated how changing the analysis objective and accounting for probabilistic characteristics radically alters the hierarchy of key concepts. This indicates the relative nature of centrality and paves the way for the creation of context-dependent and more precise metrics of influence. The results are significant for the analysis of information-psychological operations, the development of mechanisms to counter cognitive warfare, and strategic planning in the field of national security.
Keywords: semantic-probabilistic centrality, SBC, PSBC, betweenness centrality, cognitive warfare, cybersecurity, information chains, semantic network.

Introduction

The analysis of complex networks is a key tool for understanding the structure and dynamics of information, social, biological, and technical systems. One of the central directions of this analysis is the identification of nodes that play the most important role in the functioning of a network. This role is traditionally evaluated using centrality metrics – such as degree centrality, closeness centrality, betweenness centrality, eigenvector centrality, etc. These metrics are successfully applied in various fields – from sociology to cybersecurity – to identify influential actors, critical infrastructure elements, or key concepts in cognitive systems.

The betweenness centrality metric is particularly powerful, as it measures the number of shortest paths between pairs of nodes that pass through a given node. It effectively identifies "bridges" in the network – nodes that control the flow of information or influence. However, this classical metric is based exclusively on the topological structure of the network: it assumes that all paths are equivalent, and only their geometric path is important. In real-world applications, especially in information and cognitive systems, such an assumption is often too restrictive.

In such systems, paths between nodes carry semantic weight. For example, in the context of cognitive warfare, chains of influence are evaluated not by their length, but by criteria such as resistance to countermeasures, scale of impact, resource intensity, implementation time, or legitimacy. This means that the most important path may not be the shortest one, but, for instance, the most resilient or the most large-scale. Accordingly, a node that lies on such paths becomes important from the perspective of centrality, but only within the context of this specific semantics.

Currently, research on centrality focuses primarily on topological or weighted graphs, where edge weights reflect distance, time, or cost. For example, Freeman [1] laid the foundations of betweenness centrality, Newman [2,3] provided calculation algorithms and generalized it for weighted networks, and Brandes [4] proposed efficient algorithms for its computation. However, these approaches do not account for the semantic diversity of paths – that is, the fact that different paths can be "optimal" according to various content-based criteria, even if their topological lengths are identical.

The emergence of Large Language Models (LLMs) has opened fundamentally new opportunities for the construction and analysis of semantic networks. It is now possible to rapidly and automatically generate complex cause-and-effect structures by integrating knowledge from various sources and uncovering hidden connections between abstract concepts [5, 6]. In particular, the approach based on the "swarm of virtual experts" concept [7] allows for repeatedly querying LLMs to generate diverse interpretations, which are then aggregated into a single semantic network, ensuring both the depth and completeness of the model.

Furthermore, LLMs enable not only the construction of networks but also the assessment of qualitative characteristics of paths – for instance, their resilience, emotional charge, or cultural legitimacy. This makes it possible to combine formal graph analysis with semantic evaluation, which is critically important for analyzing complex phenomena such as information-psychological warfare [8, 9].

In this article, we propose a new approach to measuring centrality, based on the idea of semantic betweenness. We consider the concept of semantic betweenness centrality (SBC) – a separate metric for each semantic criterion, which determines how often a node lies on paths that are optimal according to that specific criterion. Such an approach allows the network to be analyzed not from a single, universal perspective, but from multiple context-dependent perspectives.

The main idea is that centrality is not an absolute property of a node, but a relative characteristic that depends on the objective of the analysis. A node can be key in chains aimed at achieving resilient influence, and completely unnoticeable in chains oriented toward rapid execution. This makes the proposed approach particularly relevant for analyzing complex information strategies, such as cognitive warfare, where the importance of system elements is determined not only by their topological position but also by their substantive contribution to achieving specific goals.

Specifically, in the field of cybersecurity, this approach enables the detection of not only technical infrastructure vulnerabilities but also hidden semantic attack chains, such as social engineering or cognitive manipulations, which frequently precede sophisticated cyber intrusions.

The objective of this article is to propose a mathematically rigorous model of semantic betweenness centrality, demonstrate its application using a cognitive warfare network as an example, and show how changing the semantic criterion leads to a radical shift in the hierarchy of key nodes. The research results confirm that traditional centrality metrics are insufficient for analyzing semantically enriched networks and pave the way for the creation of context-dependent tools for influence analysis.

1. Formation and Analysis of a Semantic Network

1.1. Semantic Networks as a Tool for Analyzing Complex Systems

Modern information, social, biological, and cognitive systems are characterized by a high level of complexity, multi-level structures, and rich semantic content. For their analysis, semantic networks are increasingly being used – graph models in which nodes represent notions, concepts, or entities, and edges represent semantic, logical, or causal relationships between them.

Unlike traditional topological networks, where only the structure of connections is important, semantic networks take into account the substantive nature of paths. This allows for modeling not just "who is connected to whom," but, for example, "how one idea influences another," "how a strategy is implemented through mechanisms," or "how a goal is achieved through a chain of actions."

In such a network, classical centrality metrics – degree, closeness, and betweenness – remain important but insufficient. They do not account for the qualitative properties of paths that determine their actual effectiveness in a specific context.

1.2. Construction of a Semantic Network

There are many ways to form semantic networks: manual expert curation, text analysis, knowledge extraction from databases, and automated document parsing. In this work, we propose one of the possible approaches, which becomes particularly effective when combined with modern technologies – the use of large language models (LLMs) for the automated expansion of a hierarchical model. This approach is not universal, but it demonstrates high flexibility, speed, and depth in constructing complex semantic structures, especially in cases where it is necessary to quickly generate many logically interconnected ideas.

1.3. The Concept of a "Swarm of Virtual Experts"

The key idea of this concept is the simulation of collective expert activity using LLMs. Since the same model can generate different responses to the same question, we can engage it in various roles, creating an artificial "swarm of virtual experts." Furthermore, during research, one can also query dozens of different LLMs. This approach can be implemented in the following way:

1. Initial Hierarchical Model

We begin with a small yet conceptually complete model – a set of key concepts and the relationships between them. For example, in a general case, this may take the form:

“Goals” → “Means” → “Mechanisms” → “Consequences”.

2. Systematic Expansion

For each node in this model, a prompt is submitted to the LLM in the following format:

“For the concept 'X' within the context of 'Y', identify up to 3 new concepts (1–3 words) that specify it. Provide the output as pairs: 'X; New Concept'.”

For instance, for the node “Methods of Influence” in the context of “information warfare”, the model may suggest:

– Methods of Influence; Disinformation

– Methods of Influence; Emotional Manipulation

– Methods of Influence; Fake News.

3. Iterative Prompting with Varied Roles

To mitigate bias and enhance diversity, the prompt is submitted multiple times, each time assigning a different “role”:

– “You are a psychologist specializing in mass behavior.”

– “You are a historian and propaganda expert.”

– “You are an information operations strategist.”

This approach enables the generation of diverse, in-depth, and interdisciplinary responses that accurately reflect the multifaceted nature of the phenomenon.

4. Aggregation and cleaning

All generated pairs are collected, duplicates are removed, and statistical and expert filtering is performed (removing illogical or overly distant connections), after which a complete semantic network is formed.

5. Result

The output is a directed graph $G = (V, E)$, where V is a set of nodes (concepts), and E is a set of directed edges (connections of the type "general → specific" or "cause → effect"). Such a network can contain hundreds of nodes and connections, serving as a foundation for further analysis.

1.4. Example: Semantic network of cognitive warfare

To illustrate the proposed approach, we consider the construction of a semantic network of cognitive warfare. This is not the only possible case, but it effectively demonstrates the capabilities of the method.

The initial model includes five levels: from the general phenomenon "Cognitive warfare" to specific "Consequences", such as

"Collective amnesia" or "Loyalty to the aggressor". This model is conceptually complete but contains only the primary links.

Using the "swarm of virtual experts" concept, the model was expanded. For each node, new, more specific concepts were generated. For example, for "Actors' goals", the following were obtained: "Destruction of national identity", "Formation of false worldviews", "Deconstruction of mythology", etc.

As a result, a complete network was constructed, containing 290 nodes and 310 connections (Fig. 1). This network serves as an ontology of cognitive warfare, encompassing not only general categories but also specific mechanisms, tools, and scenarios of influence.

2. Centrality Metrics and Semantic Reinterpretation of Betweenness

To analyze the structural role of nodes within the constructed semantic network, classical centrality metrics are applied. They enable the identification of concepts that play a key role in the system of informational influence. Below are the three most common metrics utilized in this study.

Figure 1. Semantic network "Cognitive Warfare"

2.1. Primary Centrality Metrics

1. Out-Degree Centrality

It determines the number of direct consequences originating from a given node. For a node v in a directed graph $G = (V, E)$:

$$Cout(v) = |\{u \in V \mid (v,u) \in E\}|.$$

This metric indicates the sources of influence initiation – concepts that generate many other ideas. For example, concepts such as "Introduction of false scientific theories" or "Introduction of false paradigms" exhibit a high out-degree.

2. Eigenvector Centrality

It accounts not only for the number of connections but also for the importance of neighboring nodes. It is defined as the principal eigenvector of the adjacency matrix $\boldsymbol{A}$:

$$Ax = \lambda x, \; C_{eig}(v)=x_v,$$

where λ is the largest eigenvalue, and x is the corresponding eigenvector. This metric identifies ideological cores – concepts that are not merely targets but are also supported by numerous other chains. For example, the "Theory of Official Nationality" has a high C_{eig} value, as it is integrated into many different scenarios.

3. Betweenness Centrality – Classical Version

The most relevant metric for analyzing influence flows is betweenness centrality, which measures how frequently a node lies on the shortest (geodesic) paths between other pairs of nodes. Let σ_{st} be the total number of shortest paths between nodes s and t, and $\sigma_{st}(v)$ be the number of such paths that pass through v. Then:

$$C_B(v) = \sum_{\substack{s,t \in V \\ s \neq t \neq v}} \frac{\sigma_{st}(v)}{\sigma_{st}}.$$

This metric identifies "bridges" in the network – concepts that connect different levels or domains of influence. For example, "Introduction of false paradigms" exhibits a high C_B, as it connects general goals with specific tools.

2.2. Semantic reinterpretation of betweenness

In the context of cognitive networks, the shortest path is not always the most important one. The importance of a path is determined not only by its length but also by semantic properties that define its effectiveness within a specific strategy. In particular, the following criteria can be introduced:

– Resistance to counteraction (R) – how difficult it is to neutralize the chain.
– Scale of impact (S) – whether the path operates at a local, national, or global level.
– Resource intensity (C) – the amount of resources required for implementation.
– Path length (L) – the number of transitions (as in the classical case).

This means that instead of counting the shortest paths, one must count the paths that are optimal according to a specific semantic criterion. Let a set of paths P_{st} leading from s to t be defined for each pair of nodes $s, t \in V$. For each criterion $q \in\{R, S, C, L\}$, a set of optimal paths can be defined as:

$$P_{st}^{(q)} = \left\{ p \in P_{st} \mid q(p) = opt_q\left(\left\{q(p') \mid p' \in P_{st}\right\}\right)\right\},$$

where opt_q is the optimization operation for criterion q: maximization for R and S, and minimization for C and L.

To find opt_q, the following steps are performed: we collect the values of criterion q for all paths between s and t, find the optimal value (the minimum or maximum, depending on q), and select all paths that achieve this optimal value.

Let:

– $\sigma_{st}^{(q)} = \left|P_{st}^{(q)}\right|$ be the number of paths between s and t that are optimal according to q,
– $\sigma_{st}^{(q)}(v)$ be the number of such paths that pass through v.

Then, the semantic betweenness centrality according to criterion q is defined as:

$$C_B^{(q)}(v) = \sum_{\substack{s,t\in V\\ s\neq t\neq v}} \frac{\sigma_{st}^{(q)}(v)}{\sigma_{st}^{(q)}}.$$

This formula is a generalization of the classical betweenness concept, where semantically optimal paths are used instead of geodesic paths.

Each $C_B^{(q)}$ corresponds to a specific logic of influence, for example:

– $C_B^{(R)}$ it shows which nodes are most critical for resilient chains that are difficult to neutralize;
– $C_B^{(S)}$ it identifies which nodes are key for large-scale, widespread operations;
– $C_B^{(C)}$ it indicates which nodes are utilized in economical, resource-saving scenarios;
– $C_B^{(L:)}$ it determines which nodes control the fastest, most direct paths.

2.3. Probabilistic Semantic Betweenness Centrality (PSBC)

Counting the number of optimal paths has a significant limitation: it treats all paths that achieve the optimal value for criterion q as equivalent. In real cognitive or cybernetic systems, this is not the case. Even among semantically optimal paths, there are those that are more likely to be realized due to structural or resource constraints.

To overcome this limitation, it is proposed to integrate a logical-probabilistic model, similar to the MRRW-PageRank approach [10], where link weights and node importance are determined iteratively and interdependently. In such an approach, betweenness is accounted for not merely by the fact of a node's presence on an optimal path, but proportionally to the probability of traversing that specific path. This allows for filtering out "theoretically optimal" but improbable chains of influence, focusing attention on genuinely threatening or the most effective semantic trajectories.

This approach logically combines the semantic criterion in SBC with the link weighting mechanism from the study on MRRW-PageRank. As a model, this approach is implemented through the following steps:

Step 1: Determination of the semantic link weight

Let us assume that for a given semantic criterion q (e.g., resistance or scale), each node j has a specific semantic score $Score_q(j)$. The weight w_{ij}^q of a directed link from node i to node j is defined as a function of the target node's importance and its in-degree $d_{in}(j)$ (the number of paths leading to j), which models the "dilution" of attention or resources:

$$w_{ij}^q = \frac{Score_q(j)}{d_{in}(j)}.$$

Obviously, the higher the semantic value of the node j for achieving the goal q, the more attractive the path to it becomes. However, if many paths lead to the node (a large in-degree $d_{in}(j)$), the weight of each individual incoming link decreases, as it is less unique or more dispersed.

Step 2: Transition probability and path probability

Based on the link weights, a transition probability matrix P_q is constructed. The probability of transitioning from i to j, given the current state at i, is:

$$P_{ij}^q = \frac{w_{ij}^q}{\sum_{k \in Out(i)} w_{ik}^q}.$$

Then, the probability of realizing a specific path $p = (v_0, v_1, ..., v_k),$, which is optimal according to the criterion q, is defined as the product of the transition probabilities along this path (logical-probabilistic model):

$$Prob_q(p) = \prod_{m=1}^{k} P_{v_{m-1}v_m}^q.$$

Step 3: Probabilistic Semantic Betweenness Centrality (PSBC)

Instead of a simple ratio of path counts $\frac{\sigma_{st}^q(v)}{\sigma_{st}^q}$, PSBC is introduced, which sums the probabilities of those optimal paths passing through node *v*, normalized by the total probability of all optimal paths between *s* and *t*:

$$PSBC_q(v) = \sum_{s \neq t \neq v} \frac{\sum_{p \in P_{st}^q(v)} Prob_q(p)}{\sum_{p \in P_{st}^q} Prob_q(p)},$$

where P_{st}^q is the set of all paths between *s* and *t* that are optimal according to the semantic criterion *q*; $P_{st}^q(v)$ is the subset of these optimal paths that pass through node *v*; and $Prob_q(p)$ is the probability of the realization of path *p*, calculated based on the interdependent weights of the links.

The proposed model can be made iterative by implementing the following steps:

1. Initial assessment of node values $Score_q$.
2. Calculation of edge weights w_{ij}^q and path probabilities.
3. Updating node $Score_q$ values based on their new $PSBC_q$ [centrality scores/weights] (a node becomes more important if the most probable optimal paths pass through it).
4. Repeating the process until convergence.

2.4. Multiplicity of Centralities

Since there can be a multitude of semantic criteria for path optimality – such as resistance to counteraction, scale of impact, time, risk, legitimacy, emotional charge, cultural depth, ethical acceptability, etc. – each such criterion yields a distinct node centrality measure.

In other words, there is no single, universal centrality. Its meaning is determined by the research objective, for example:

– if the goal is to identify the fastest paths to "Collective amnesia", the key metric will be $C_B^{(L:)}$;

– if the goal is to identify the most resilient paths, then $C_B^{(R)}$;

– if the goal is to identify the least resource-intensive paths, then $C_B^{(C)}$;

– if the goal is to identify the most emotionally charged paths, then $C_B^{(emotion)}$.

This implies that the number of possible centralities is limited only by the number of ways in which path "optimality" can be interpreted. Consequently, centrality is not merely an inherent property of a node, but also a reflection of the analytical objective.

3. Empirical Analysis: Variability of Node Centrality Depending on Path Semantics

Based on the theoretical foundation outlined in the previous section, we proceed to the empirical analysis, the objective of which is to demonstrate how the same node can occupy different positions in the hierarchy of key concepts depending on the semantic criterion of path optimality used to determine semantic betweenness centrality (*SBC*).

For this purpose, the complete set of paths leading from the initial state "Cognitive warfare" to the target state "Collective amnesia" was utilized. These paths were identified through graph traversal (e.g., using the Depth-First Search (*DFS*) algorithm) within an extended semantic network comprising 290 nodes and 310 edges.

For each path, the following semantic criteria were evaluated, as defined in this study:

– Length (*L*) – the number of transitions (edges) in the path (minimized).

– Resistance to counteraction (*R*) – a score from 1 to 5 indicating the difficulty of neutralizing the path.

– Resource capacity (*C*) – a score from 1 to 5, where 1 represents low resource expenditure and 5 represents high expenditure.

– Scale of impact (*S*) – 1 (local), 2 (national), 3 (global).

For each criterion $q \in \{L, R, C, S\}$, a set of optimal paths $P(q)$ was determined, comprising those paths that achieve the optimal value for criterion q (minimized L, maximized R, minimized C, maximized S). Subsequently, the *SBC* value for each node v was calculated according to criterion q.

Below (Table 1), the calculation results are presented for four key nodes that frequently appear in the paths leading to the target state of "Collective amnesia".

The PSBC metric "penalizes" paths that are theoretically optimal but improbable under real-world conditions (e.g., fast but easily refutable), while "amplifying" the weight of nodes that form part of resilient, systemic, and highly probable chains of influence (Table 2).

Table 1. Semantic Betweenness Centrality (SBC) and node ranks according to different criteria

NODE	SBC_L	RANK SBC_L	SBC_R	RANK SBC_R	SBC_C	RANK SBC_C	SBC_S	RANK SBC_S
Introduction of false scientific theories	0.88	2	0.32	18	0.75	3	0.40	12
Theory of Official Nationality	0.15	47	0.92	1	0.15	47	0.89	2
Art	0.65	8	0.50	8	0.60	7	0.70	5
Erosion of critical thinking	0.40	15	0.25	25	0.80	4	0.30	18

Table 2. Probabilistic Semantic Betweenness Centrality (PSBC) and node ranks according to different criteria

NODE	$PSBC_L$	RANK $PSBC_L$	$PSBC_R$	RANK $PSBC_R$	$PSBC_C$	RANK $PSBC_C$	$PSBC_S$	RANK $PSBC_S$
Introduction of false scientific theories	0.42	16	0.21	32	0.38	22	0.28	26
Theory of Official Nationality	0.12	45	0.96	1	0.19	36	0.93	2
Art	0.58	10	0.56	7	0.55	9	0.74	4
Erosion of critical thinking	0.51	13	0.33	21	0.86	3	0.48	11

4. Analysis of Results

The comparative analysis of semantic (SBC) and probabilistic semantic (PSBC) betweenness centrality metrics for four key concepts leading to the target state of "Collective amnesia" clearly demonstrates the filtering and refining capabilities of the proposed model. The introduction of path realization probability radically alters the node hierarchy, filtering out "paper" (theoretical) optimality in favor of identifying genuine threats.

"Introduction of false scientific theories"

This concept experienced the most significant drop in rankings when transitioning from SBC to PSBC. Although under the deterministic SBC metric it ranked second in realization speed (L, rank 2) and third in resource efficiency (C, rank 3), the PSBC model sharply reduced its weight (e.g., to 32nd place for resilience R and 26th for scale S). This is because pseudoscientific constructs, while potentially short, have a low probability of successful realization due to the high risk of exposure (fact-checking), resistance from the academic community, and the need to artificially sustain complex narratives. PSBC correctly identifies this path as "fragile" and improbable in the long term, despite its formal optimality.

"Theory of Official Nationality"

Conversely, this concept confirmed and even slightly strengthened its position as the most realistic systemic threat. Its indicators for resistance to counteraction (R, 1st place) and scale of impact (S, 2nd place) remained consistently high in both models. This is because state or systemic ideological constructs have a high a priori probability of realization due to institutional, financial, and administrative support, even if they are resource-intensive (low rank for C) and long-term (low rank for L). PSBC validates this concept as the most probable and stable trajectory for long-term influence.

"Art"

This node demonstrated the highest stability, retaining its status as a universal vector of influence (ranks 4 to 10 across all criteria in PSBC). The probabilistic assessment confirmed that cultural and artistic chains are not only large-scale but also highly probable due to their indirect, emotional, and organic reception by the target audience. Unlike direct propaganda, artistic narratives are harder to identify as hostile actions, which naturally increases the probability of their successful progression to the final goal without active resistance.

"Erosion of critical thinking"

This concept showed an increase in probabilistic weight according to the resource capacity criterion (rising from 4th to 3rd place in PSBC), while remaining weak in resilience and scale as an isolated factor. Since the manipulation of basic cognitive biases is the simplest, cheapest, and most mass-scale tool, the probability of traversing exactly such paths is extremely high. PSBC correctly highlights that this is the most probable "entry point" for a cognitive attack, which prepares the ground for the implementation of more complex ideological constructs.

The comparison of the SBC and PSBC tables convincingly demonstrates that formal topological or semantic optimality (SBC) does not guarantee real effectiveness under conditions of counteraction. The introduction of probabilistic weight (PSBC) allows the analyst to distinguish concepts that are optimal only in graph theory from those that are truly the most probable channels of influence in real-world conditions of hybrid confrontation. This makes the proposed model suitable not only for the retrospective analysis of networks but also for building prognostic scenarios and prioritizing information security and cybersecurity measures.

Conclusions

In this paper, we propose a novel approach to analyzing node centrality in semantic networks, based on a rethinking of the classical betweenness centrality metric. Instead of identifying key nodes exclusively by the number of shortest paths passing through them, we consider centrality as a quantity that depends on the semantic properties of the paths – such as resistance to counteraction, scale of impact, resource capacity, or implementation time. This allows for the determination of semantic betweenness centrality (SBC) for each specific path optimality criterion, thereby formalizing the idea that a node's importance is determined not only by its topological position but also by its role in the context of a specific strategy.

A crucial step in the development of the proposed methodology was the introduction of probabilistic semantic betweenness centrality (PSBC). Unlike SBC, the PSBC model integrates an iterative logical-probabilistic approach that accounts not only for the fact of a node's presence on an optimal path but also for the actual probability of that specific path being traversed. This effectively filters out improbable theoretical chains, focusing the analyst's attention on the most effective and genuinely threatening semantic trajectories, which significantly enhances the model's adequacy to real-world processes.

Empirical analysis has shown that the same node can occupy either leading positions or significantly lower ranks in the centrality hierarchy, depending on the chosen semantic criterion and the consideration of probabilistic weights. This result highlights the relative nature of centrality in complex information systems and indicates the limitations of traditional metrics in cases where the analysis requires accounting for the substantive and probabilistic aspects of interactions.

The novelty of this work lies in the generalization of the centrality concept through the consideration of a set of independent SBC metrics and the introduction of PSBC for building multidimensional models of influence. This approach provides a method by which an analyst can select priorities based on the research objective – whether it is searching for the most resilient chains, the most resource-efficient ones, or the most probable attack scenarios.

Future research prospects involve expanding the set of semantic criteria, automating their determination, and calibrating probabilistic weights using Large Language Models (LLMs), as well as developing visualization tools and centrality vector comparison methods for strategic analysis.

In particular, the integration of the proposed PSBC metrics into cybersecurity systems will enable the proactive detection and neutralization of hybrid threats, in which technical cyberattacks are combined with targeted cognitive manipulations of personnel or end-users.

The obtained results are significant for understanding the structural role of concepts in complex information systems and can be utilized to enhance the effectiveness of countering destructive influences, particularly in the context of cognitive aggression.

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