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Research Article

Unlocking the dynamics of open innovation: A conceptual exploration

Açık inovasyonun dinamiklerini ortaya çıkarmak: Kavramsal bir keşif

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Abstract

This study explores the complex domain of open innovation, a conceptual framework in which the word "open" signifies sharing tacit organisational knowledge. Organisations increasingly expand their scope outside conventional bounds by using open innovation approaches and models to acquire necessary resources. The main aim of this academic undertaking is to examine informal networks that arise outside traditional contractual agreements and then analyse the tangible structure of these networks. The study's primary objective is to thoroughly examine, compare, and analyse nonlocal centrality measures, including global and local viewpoints, within a conceptual framework. This research investigates the utilisation of network analysis methodologies, such as Degree Centrality, Closeness Centrality, Eigenvector Centrality, Betweenness Centrality, Modularity, Community Detection, Vote Rank, and Digital Flaneurs, through the implementation of the Python NetworkX Programming Language. This research highlights its conceptual relevance as a significant and considerable addition to the current body of knowledge. This study provides a fundamental basis for further investigating and comprehending the complex interplay of nonlocal centrality measurements, dynamic capabilities, and open innovation tactics. Therefore, this study is a noteworthy contribution to the scholarly body of knowledge, presenting useful perspectives on the complex relationship between open innovation approaches, dynamic capabilities, and nonlocal centrality measurements. Furthermore, this research adds to the wider scholarly discourse on how organisations effectively manage the intricate challenges of the modern digital environment to achieve innovation and maintain a competitive edge.

Keywords: Network Analysis, Nonlocal Centrality Measures, Open Innovation, Digital Transformation, Strategy and Management

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Öz

Son Bu çalışma, açık inovasyonun karmaşık alanlarını keşfetmeyi amaçlamaktadır. "Açık" kelimesi, örgütsel bilginin açıkça paylaşılma eylemini ifade eder. Organizasyonlar, geleneksel sınırları aşmak ve gerekli kaynakları elde etmek amacıyla açık inovasyon yaklaşımlarını benimseyerek genişlemektedir. Çalışmanın temel amacı, global ve yerel bakış açıları içeren bir kavramsal çerçeve içinde nonlocal merkeziyet ölçümlerini kapsayan detaylı bir inceleme, karşılaştırma ve analiz sunmaktır. Python NetworkX Programlama Dili kullanılarak, Degree Centrality, Closeness Centrality, Eigenvector Centrality, Betweenness Centrality, Modularity, Community Detection, Vote Rank ve Digital Flaneurs gibi ağ analizi metodolojilerinin kullanımını araştırmaktadır. Bu çalışma, nonlocal merkeziyet ölçümleri, dinamik yetenekler ve açık inovasyon stratejileri arasındaki karmaşık etkileşimi daha iyi anlamak ve incelemek amacını taşımaktadır. Dolayısıyla, açık inovasyon yaklaşımları, dinamik yetenekler ve nonlocal merkeziyet ölçümleri arasındaki bu karmaşık ilişki üzerine sağladığı değerli bakış açılarıyla bilimsel literatüre önemli bir katkı sunmaktadır. Ayrıca, bu araştırma, organizasyonların modern dijital ortamın getirdiği karmaşık zorlukları etkili bir şekilde yönetme, yenilik elde etme ve rekabet avantajını sürdürme konusundaki geniş bilimsel tartışmalara da katkıda bulunmaktadır.

Anahtar Kelimeler: Ağ Analizi, Non-Local Merkeziyet Ölçüleri, Açık İnovasyon, Dijital Dönüşüm, Strateji ve Yönetim

JEL Kodları: M10, O33, C80

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Unlocking the path to sustainable success: A synergy of digital transformation and intellectual capital

In today's competitive landscape, organizations must expand their workforce and adapt to contemporary trends to maintain their competitive edge. A meticulously crafted strategic plan is the linchpin for success in this dynamic environment. In their recent study, Wasono et al. (2022) underscore the pivotal role of accumulating intellectual capital as a cornerstone for long-term business success, particularly amid relentless economic competition and globalization. This study delves into the intricate relationship between the requisites of digital transformation and the components of intellectual capital. Employing graph analysis and organizational network analysis (ONA), the research meticulously dissects the interplay between these elements. It introduces six overarching conceptual frameworks: integration, driving, driving, stability, criticality, and precariousness. These frameworks shed light on the intrinsic value that digital transformation injects into intellectual capital.

Moreover, the study explores the ability of organizations to interact and identifies those that exhibit resilience and influence, as well as those poised to fill structural gaps within networks. The stability feature, specifically, helps identify companies of paramount significance, acting as crucial launch points for the initiation of digital transformation endeavors. The study's findings underscore the profound significance of digital transformation and its alignment with the components of intellectual capital, providing organizations with invaluable insights as they strive to prosper in the ever-evolving business landscape. The intricate interconnectedness between the digital transformation criteria and intellectual capital components acts as a guiding map for strategic planning and execution. Ultimately, this synergy fortifies an organization's capacity to survive and thrive in a fiercely competitive environment. As organizations navigate the complex terrain of modern business, this research equips them with a robust framework for strategic decision-making, propelling them towards sustained success.

Integration: The Critical Role of Integration in Sustaining System Integrity and Facilitating Interconnections

In systems theory, system integrity pertains to how various elements, such as nodes, graphs, and subsystems, contribute to a system's overall coherence and robustness. This fundamental attribute is pivotal in system analysis and design and has been scrutinised in academic and practical contexts. High levels of integration within a system signify how a particular unit or component actively contributes to upholding the system's overall integrity. This pertains to its capacity to sustain the functionality of the system and create connections and interactions with other elements, thereby promoting a unified and synergistic whole (Turnbull, 2018). Integration is intrinsically tied to the system's stability, adaptability, and efficiency. Conversely, a low degree of integration indicates the presence of discrete entities or subsystems that operate with limited connection-making capabilities. These entities function relatively independently and may lack the ability to form meaningful relationships or collaborations with other components. Such a lack of integration can result in fragmentation and inefficiency within the system, potentially hindering its overall performance and adaptability. Furthermore, the concept of integration capacity, as articulated by Baskici and Ercil in their work in 2018, adds a nuanced layer to our understanding. It can be viewed as the minimum effective information ratio required for achieving node coherence within a specific community or subset of a larger system. This metric becomes instrumental in categorising and organising subsets within the broader system, helping delineate the boundaries and interdependencies among different components.

In summary, the degree of integration within a system plays a fundamental role in shaping its integrity and functionality. Understanding how integration contributes to system coherence and interconnectivity is paramount for system analysts, designers, and organizations aiming to enhance operational efficiency and adaptability. This comprehensive exploration sheds light on the multifaceted nature of integration within the context of system integrity.

Driving: Enhancing System Functionality through Active Communication Values

Within the intricate landscape of systems analysis, the driving force that propels nodes and graphs to influence and activate other components within a system is a pivotal determinant of its overall efficiency and functionality. This principle of activation is paramount, with practical implications for various applications. The influence a node or graph exerts within a system is gauged by its ability to stimulate the activation of other nodes and graphs, thereby setting a chain reaction of interactions and information flow in motion. This attribute lies at the heart of dynamic systems, where effective communication and interactivity are crucial for the system's success and adaptability.

A noteworthy distinction within this context is the differentiation between active and passive communication values. Active communication values are highly favoured in this paradigm over their passive counterparts. Numerical values that trend towards higher scales indicate greater effectiveness in driving system dynamics and facilitating interactions among various components. Systems characterized by such high values of activation not only ensure the efficient distribution of information but enable seamless coordination and responsiveness across the entire system. This preference for higher activation values finds resonance in specific applications where efficient communication and rapid response are paramount. The research conducted by Faith et al. in 2022 underscores the significance of this paradigm in contemporary systems theory and practice.

In conclusion, the concept of driving factors in system dynamics, as related to node and graph activation, represents a critical aspect of systems analysis and design. The emphasis on active communication values and their influence on system performance offers valuable insights for various applications, from technological systems to organizational networks. Understanding the role of driving factors and their impact on system dynamics is instrumental in optimizing performance and adaptability in complex systems.

Driven: Understanding the Impact of Passive Communication Values and the Nature of Driven Components

In system dynamics, passive communication revolves around how a node and its associated graph can be influenced or altered by another node within the system. This concept bears significant implications for assessing the effectiveness of various methodologies and understanding the dynamics of system behaviour. In the context of passive communication, the value assigned to this attribute is a key aspect. High passive communication values are particularly important, as they indicate the system's ability to adapt and respond to external influences and interactions. Such values are instrumental in identifying accomplishments and assessing the robustness of system methodologies. The ability of a system to be receptive to change and to adjust its behaviour in response to external factors is a hallmark of its adaptability and effectiveness. The study carried out by Leito and Baptista in 2018 illuminates the process of identifying nodes and graphs within a system that are particularly vulnerable to indirect connections and external influences. This insight highlights the intrinsic nature of driven components within the system—elements more amenable to transformation and change. Recognizing such driven components is essential for understanding the system's dynamic behaviour.

Moreover, the initial transformation of the first component within the system is a critical juncture that can manifest oscillatory behaviour. This behaviour, characterized by recurring fluctuations and adjustments, underscores the interplay between driving and driven components within the system. In summary, the concept of passive communication and the role of driven components offer valuable insights into the dynamics of complex systems. Understanding the extent to which external influences can alter elements within a system is integral to system analysis and design. This knowledge enhances our ability to assess methodologies' adaptability and resilience and grasp dynamic systems' oscillatory nature. The research by Leito and Baptista in 2018 contributes to a deeper understanding of these fundamental dynamics within complex systems.

Stability: Understanding the Dynamics of Stable and Dynamic Systems

System stability is fundamental to understanding how a system behaves and responds over time in dynamic systems. It pertains to the system's ability to maintain its behaviour within a specified range and magnitude, following predetermined motion patterns. Stable systems are characterized by their capacity to produce consistent and predictable outcomes, a quality highly valued in various domains. However, it is crucial to recognize that pursuing stability has limits. When a system achieves and maintains stability beyond a certain threshold, it may inadvertently lead to a state of institutional rigidity. In this state, actors' reactions within the system to external changes or stimuli become resistant or impervious to alteration.

Over time, this institutional rigidity can erode the adaptability and responsiveness of the system, potentially compromising its overall integrity. On the other hand, when stability within a system decreases below a certain threshold, it signifies a shift towards dynamism. In dynamic systems, adapting and accommodating changes is a hallmark. This dynamism allows the system to respond flexibly to evolving conditions and challenges, ensuring its continued relevance and effectiveness (Emmerik et al., 2016). Understanding the delicate balance between stability and dynamism is crucial for effectively managing and designing systems across various domains. Striking the right equilibrium between maintaining predictability and embracing adaptability is essential for systems' long-term success and resilience. The research by Emmerik and colleagues in 2016 provides valuable insights into the dynamics of system stability, shedding light on the implications of stability thresholds and the importance of adaptability within complex systems.

Criticality: Understanding the Influence of Critical Elements on System Transformations

In system dynamics, criticality is central in assessing the significance of nodes and graphs within a given system. Criticality serves as the key determinant of the relevance of these elements, playing a crucial role in shaping the dynamics and adaptability of the system. The degree of criticality exhibited by a system is intimately linked with its susceptibility to alterations and changes. Systems with higher degrees of criticality are more vulnerable to external influences and internal modifications. These systems are finely balanced and sensitive, making them more responsive to various factors that can trigger transformations. Of note is the unit within the system that demonstrates the highest degree of criticality. Often called the most influential agent, this unit wields substantial power in driving system transformations.

According to the research conducted by Hütt and colleagues in 2016, every alteration made to this critical unit carries significant implications for the overall system. Changes to this pivotal element can create a cascade of effects, potentially leading to substantial shifts in system behaviours and outcomes. Understanding the concept of criticality is paramount for system analysts and designers. It sheds light on the elements that hold the key to system adaptability and transformation. By identifying and comprehending the most critical components, practitioners can make informed decisions to effectively manage and direct system dynamics.

In summary, criticality is pivotal in system dynamics, determining the relevance and influence of nodes and graphs. It offers a unique perspective on the sensitivity and susceptibility of systems to change, highlighting the significance of identifying and managing critical elements. The research (Hütt et al., 2016) contributes to our understanding of the profound impact of highly critical units on overall system transformations. Their criticality determines the relevance of nodes or graphs in a system. The degree of criticality shown by a system is directly correlated with its susceptibility to alterations. The unit exhibiting the highest degree of criticality is the most influential agent in transforming systems. According to Hütt et al. (2016), every alteration made to this unit significantly impacts the overall system.

Precarious understanding of the instability of units, openness to cooperation, and the role of centrality in network analysis

Within the intricate realm of complex systems, precarious behaviour sheds light on conduct that lacks stability, rendering individuals or units unpredictable due to significant volatility. This instability is rooted in the units' internal structural dynamics rather than solely a result of environmental factors. The instability within units serves as a critical indicator, offering insights into their openness to external cooperation and transformative potential. A minimal level of instability signifies closely guarded units and resistance to interactions outside the system. It indicates a hesitance to participate in external collaboration or adjust to evolving circumstance. In contrast, actors demonstrating a substantial degree of hesitancy exhibit honesty, effective communication, and a willingness to clarify and elucidate behavioural changes.

These individuals may act as catalysts for transformative processes within the system, leveraging their adaptability and openness to external influences. In network analysis, which examines social processes using networks and graph theory, a wide array of methodologies and theoretical frameworks are integrated to analyse complex relationships and interactions. One of the key aspects of network analysis is the centrality of nodes or elements within the network. The importance of centrality varies depending on the specific context and can be evaluated through different metrics. Four commonly used centrality measures in network analysis are degree centrality, closeness centrality, betweenness centrality, and eigenvector centrality. Each of these metrics provides unique insights into the role and significance of nodes or elements within a network. The work by Jong and Chung in 2010 highlights the relevance of these centrality measures in the context of network analysis, shedding light on their applications and implications for understanding complex systems.

In summary, precarious behaviour and the role of units' instability within complex systems play a pivotal role in understanding volatility and the potential for transformation. The willingness to cooperate with external actors and the presence of transformation catalysts are crucial considerations. Furthermore, with its diverse centrality metrics, network analysis offers a powerful tool for dissecting the dynamics of complex systems and social processes, providing a nuanced understanding of network elements' significance and influence. The research by Jong and Chung in 2010 contributes to our comprehension of centrality in network analysis and its multifaceted applications.

A comprehensive examination of network centrality, modularity, and community detection algorithms

Network analysts often conceptualize their methodologies in terms of centrality rather than power, as they provide insights into the importance or influence of nodes within a network. The definition of "centre" varies depending on the specific method used. Using measurements of centrality rather than power offers a more precise approach to characterizing network strategies. Degree centrality considers the number of direct connections a user has with other individuals, while closeness centrality assesses an individual's proximity to other members within a network. Betweenness centrality signifies an actor's significance as a facilitator of connections between nodes. A pivotal user has strong connections with other pivotal users within the network. The conclusion section provides a detailed explanation of the study's implications in organizational terms and the interpretation of the value that digital transformation contributes to intellectual capital. The study examines six indicators: integration, driving, stability, criticality, and precariousness (Goldenberg, 2019). Degree centrality is a crucial indicator of an actor's connectivity within a network. It is determined by three factors: (1) the level of connectivity through direct edge connections to other sites, (2) the frequency with which a graph component is included in relevant paths, and (3) its proximity to other components of the graph, as measured by the average distance to the sites within the graph. Centrality indices often ascertain actors with considerable influence in a certain setting. In the context of directed networks, two distinct degree measures can be identified: in-degree and out-degree. In-degree refers to the number of connections directed towards a certain vertex, while out-degree refers to the number of connections extending outward. Centrality is often employed to describe undirected connections, while prestige is typically used to characterize directional connections (Gençer,2017).

Closeness centrality refers to the extent to which a particular actor is related to other players. "Geodesy" refers to the shortest distance between two nodes, often known as the "birds' fly distance." The aggregate geodesic distance between a given node and all other nodes within a network is calculated to quantify the ease or difficulty associated with traversing from one node to another inside a given network. The actor's proximity to other players within the network may be critical. Closeness centrality refers to the average minimum distance from a particular node to all other reachable nodes. The metric used to quantify the extent to which a node is linked to all other network nodes is called "closeness centrality." The determination of this metric involves calculating the average of the lengths covered by the shortest pathways originating from each node and extending to all other nodes within the network. The capacity of a node to receive and transmit information within a network is influenced by its proximity to other nodes. This idea, known as "closeness centrality," is fundamental in understanding the dynamics of information flow in networks. The horizon of observability posits that people inside social networks possess limited awareness of events occurring beyond a two-node distance. Closeness centrality, the opposite of centrality, quantifies the extent to which two nodes within a network are linked to one another.

In summary, a node's connectivity within a network may be determined by the extent of its direct or indirect connections to other nodes. A node's proximity indicates its capacity to retrieve information and its level of interconnectivity with other nodes within the network. A node does not necessarily need a high degree of centrality to exhibit high proximity (Gürsakal, 2009).

Eigenvector centrality is a measure that determines the prominence of an actor within a network based on their connections to other prominent users. It assigns different values to connecting links, with some edges being more important than others. Eigenvector centrality quantifies the significance of a particular node in the overall structure of a network based on the specific type of connection between them. To calculate eigenvector centrality, one must first identify the dominant eigenvalue in the pairwise adjacency matrix of the network and select the eigenvector associated with that eigenvalue. The contribution of a single node to the eigenvector centrality of a network is more significant when it has fewer links but better quality than a larger number of links with poorer quality.

Betweenness centrality refers to the level of importance an actor has as a connecting link between many networks within the framework of network theory. The term "degree of separation" refers to the numerical value that quantifies the number of intermediary actors that must be through to establish a connection between two distinct actors. Nodes with high betweenness centrality play a crucial role in facilitating communication and interaction among various individuals and organizations, exerting a substantial impact on the dissemination of information. In the same way, the concept of betweenness centrality involves identifying actors who function as intermediaries, also known as border spanners, connecting disparate segments within a graph. This metric focuses on the significance that an individual may acquire by occupying a central position within the social interactions of a network and the degree to which they are essential as a connector within a given community (Golbeck, 2013).

Vertices exhibiting high betweenness centrality possess significant influence within the organizational structure, as they can see the communications in transit and may be remunerated for transmitting the information to subsequent recipients. Therefore, these individuals possess a significant level of influence since any failure in communication would lead to their termination. In summary, eigenvector centrality and betweenness centrality are crucial metrics in understanding the significance of individuals within a network. By examining these metrics, researchers can better understand the impact of social networks on individuals and organizations, ultimately leading to more effective communication and decision-making. Degree and closeness centralities measure an actor's reachability within a network, while betweenness centrality assesses their importance based on their role as an intermediate within the network. Betweenness centrality is derived from geodesics, where an individual's significance increases if positioned along the geodesic paths connecting several pairs of actors within the network. It is often associated with the concept of critical mass and is used to determine an organization's influence or authority (Gençer, 2017).

Modularity is a metric that measures the efficacy of dividing a network into smaller subnetworks, also known as modules. Highly modular networks exhibit minimal connectivity between nodes in different modules while demonstrating strong connectivity among nodes within the same module. Various networks, including biological, chemical, sociological, computational, metabolic, and regulatory networks, naturally tend to form smaller networks, sometimes called communities or modules. Modularity in graph theory evaluates the degree of connectivity inside a certain set of nodes. Graphs with high modularity tend to harbour a substantial number of connections within a given community while displaying a relatively limited number of connections that link it to other communities. The methodology assesses the potential enhancement in the modularity score of each node by relocating to one of its neighbouring communities. To comprehensively understand modularity, it is important to thoroughly understand the concepts of homophily and assortative (Pfeffer, 2014). Homophily is often used in social network analysis, where people prefer establishing relationships with those with similar attributes, while assortative is used in ecology and epidemiology. Homophily and selectivity suggest that connections form between nodes with similar attributes or features, while modularity gives rise to homophily and selectivity.

In summary, modularity is a crucial metric for assessing the extent of network clustering and determining the effectiveness of nodes in regulating information dissemination. Understanding these metrics is essential for successful inventions and enhancing the overall efficiency of network research. Community detection identifies and categorises distinct communities within a network or social system. These communities are characterized as interconnected nodes, with most connections occurring between nodes within the same cluster. The scientific and research community has shown a growing interest in identifying communities within networks, which a group of interconnected nodes characterizes. Several algorithms have been proposed for community detection, including the spectral bisection algorithm and the Kernighan-Lin Algorithm. Graph partitioning, also known as geometric algorithm, level-structure partitioning, and multilevel algorithms, is another method used for graph partitioning. These algorithms require nodes to possess equivalent attributes and/or perform similar activities, enabling their grouping. Community detection has applications in modelling extensive internet networks and investigating social dynamics within enterprises (Al-Taie & Kadry, 2017).

The primary objective of community detection in sociology is to discern and delineate groups of individuals who exhibit similar patterns of social interactions. Various algorithms exist, including divide, aggregative, and optimization algorithms. Identifying groups of comparable nodes within a network does not always imply that these clusters must be entirely separated from one another. Instead, the promotion of "overlapping communities" is advocated as a means for organizations to facilitate the sharing of members. The Vote-Rank algorithm is a computational method that assigns a numerical rating to potential seed candidates by considering the number of votes they have received from adjacent nodes. This algorithm then clusters the candidates with the greatest rankings, increasing their separation from other seeds to minimize overlap and optimize the overall distance between them. Sophisticated seed selection algorithms are used to initiate the transmission of information by using selected nodes known as seeds. The selection of the initial set of nodes in an issue about effect maximisation poses many obstacles and offers viable solutions. The primary objective is to identify a cohort of seeds with a heightened likelihood of initiating propagation and arousing the adjacent community. Initial efforts focused on using heuristics based on degrees and centrality metrics, but the greedy strategy yielded superior performance compared to basic heuristics and generated results close to ideal. Sequence seeding, seeding timing, and adaptive seeding are alternative planting tactics that include the initial planting of just a portion of the seeds. The primary approach is to avoid sowing seeds in nodes with a substantial probability of being spontaneously triggered by their neighbouring nodes. As the investigation progressed, it became apparent that the network configuration, centrality based on entropy, and effective degree all impacted the effectiveness of sequential seeding.

Table 1: Comparison and Overarching

COMPARISON AND OVERARCHING						
Nonlocal Centrality Measures	**Global**	**Local**		**Open Innovation Strategies (Dynamic Capabilities & Prominent Features)**		
		In-Link	**Out-Link**	**Organization**	**Function**	
Degree Centrality	-Power -Prestige -importance -Structural Holes	Resilience		STABILITY		
Eigenvector Centrality	-Popularity -Prestigious	-Popularity -Prestigious	---		DRIVEN	
Closeness Centrality	-The most central	Support	Influence		DRIVEN	DRIVING
Betweenness Centrality	-Significance	Agile		STABILITY		
Modularity	-Subgraphs	Clustering according to weighted link		INTEGRATION		
Community Detection	-Subgraphs	Clustering according to link and attributions				
Vote-Rank and Network Flaneurs	-Seed Selection	Good seed or not			CRITICALLY vs. PRECARIOUS	

Source: Created by the author

Table 1 provides a comprehensive comparison and overarching overview of nonlocal centrality measures and their relevance to open innovation strategies in the context of dynamic capabilities and prominent features of organizations. It also indicates how these measures relate to specific organisational functions. Nonlocal centrality measures are examined within the dual contexts of global and local analysis. This examination considers the interpretation of open innovation strategies and dynamic capabilities, as outlined in Table 1. These centrality measures are evaluated based on graph analysis, which identifies nodes with the highest degrees of criticality, prominence, strength, significance, and prestige. The interpretation of these identified nodes aligns with the information presented in the "comparison and overarching" diagram featured in Table 1. These findings, derived from relevant literature, significantly influence understanding dynamic capabilities, distinctive organizational attributes, and nonlocal centrality measures within open innovation endeavours. This interpretative approach is guided by comparative and overarching analysis principles, thus introducing a valuable "comparison and overarching" chart. Subsequently, each organizational function and company will be discussed individually, comprehensively elucidating their interrelated aspects. Throughout this research, the investigation has consistently pursued the resolution of the research inquiry. Specifically, the study has examined the impact of digital transformation criteria on various components of intellectual capital, employing both directed edges and unilateral analyses following the study's design.

In every type of relationship, each participant typically has a well-defined role, and straying from this role is a rare occurrence, except in exceptional circumstances (López-Fernández, 2006). Across various levels of analysis, individuals, collaborators, stakeholders, and affiliated entities collaborate harmoniously to safeguard the organization's long-term prospects. The overarching goal within this extensive network is to facilitate the seamless exchange of information and optimize the utilization of all facets within the open innovation framework. Creative initiatives often demonstrate a linear or even super-linear progression in networks that rely on transmitting and exchanging information. However, the distribution of tasks, responsibilities, opportunities, and rights among network participants is characterized by a non-linear relationship.

The influence of VUCA (Volatility, Uncertainty, Complexity, and Ambiguity) is apparent in this context. Intensive interactions with stakeholders are commonplace across various domains and timeframes. During unforeseen crises, networks comprising numerous stakeholders prioritize immediate solutions over long-term strategies. This approach enhances the organization's ability to adapt swiftly, withstand challenges, and enhance its long-term sustainability. Consequently, this phenomenon not only enriches the organization's overall intellectual capacity but also affects specific organizational components, depending on the level of their active engagement. While the existing literature may not explicitly classify digital transformation as an element of intellectual capital, it is evident that it substantially contributes to the organization's overall intellectual capital. Furthermore, it significantly influences the individual components of intellectual capital, including human, structural, and relational capital.

At this juncture, the significance of network dynamics comes to the fore. The study of graph theory provides a means to comprehend the underlying dynamics, gain insights into the general structure, and address the inherent complexities of the network's nodes and edges. As proposed by Baskici and Ercil (2018), there is potential for establishing a linkage between the network analysis system, characterized by its dynamic and progressive attributes, and specific indicators using Graph Theory. The study's findings are interpreted in alignment with the six fundamental criteria established by Linss and Fried (2010), which encompass the concepts of integration, driving, driven, stability, criticality, and precariousness, as discussed in Baskici and Ercil's (2018) study.

The literature analysis underscores the necessity for metrics to assess the value contributed to the intellectual capital components in the context of airports' digital transformation requirements. The development of indicators for matrix assessment is accomplished through research queries and proposals. Baskici and Ercil (2018) introduced a set of criteria for evaluating systems and subsystems to facilitate the collective examination of existing organizational challenges and formulating future strategic decisions. A novel categorization technique based on a system matrix is proposed for system analysis. Integration pertains to the extent to which nodes, graphs, and subsystems contribute to the overall integrity of a system. The structural solutions that comprehensively encapsulate the concept of integration in network analysis include modularity and community detection. In the digital transition to intellectual capital context, assessing individual participants' contributions may result in detection status, considering weighting, attributional modularity, and community interactions. It facilitates the analysis of the integration position of each organization.

Driving refers to the primary influence of a node and graph, denoting their ability to stimulate the activation of other nodes and graphs within the given system. The study discerns the driving characteristics of a node based on its in-degree closeness and eigenvector centrality.

Driven indicates the extent to which another node may influence a particular node. Nodes with this characteristic possess significantly elevated passive communication values. Gaining insights into value is crucial for recognizing the origins of successful outcomes resulting from implemented methodologies.

System stability pertains to the stability of a dynamic system, which remains within a specified range and magnitude and follows a predetermined pattern. Stable systems are characterized by their ability to generate predictable and consistent results. The measurement of stability is ascertained through the utilization of betweenness centrality.

Criticality involves the relevance of nodes or graphs within a system, with the highest degree of criticality signifying the most influential factor in effecting significant changes in a system. Precarious behaviour is marked by instability, and predicting the behaviour of actors with a high degree of instability can be somewhat challenging. A low degree of instability indicates how close the actors are to interactions outside the system.

Conclusion

Nonlocal centrality metrics within graph theory serve as crucial tools for quantitatively assessing the significance and impact of nodes in a network, considering their associations and connections with other nodes. These metrics go beyond traditional local centrality measures like degree and proximity centrality, primarily focusing on immediate neighbours, to provide a comprehensive view of the entire network's structure. Among these metrics, betweenness centrality stands out by quantifying the extent to which a specific node serves as a bridge along the shortest paths connecting other nodes in the network. Nodes with high betweenness centrality act as pivotal points or mediators, facilitating connections across different network segments. This metric is determined by the ratio of shortest paths that pass through a particular node. Eigenvector centrality considers both direct and indirect relationships of a node, with a node's centrality score influenced by the centrality of its neighbouring nodes. Nodes connected to other nodes with high centrality will, in turn, have higher eigenvector centrality scores. PageRank, a variant of eigenvector centrality, finds particular utility in online networks. It assigns significance to nodes based on the quantity and quality of connections directed toward them, using a recursive approach where each node's importance depends on the importance of its connected nodes. This approach captures local and global effects through the exponential decay of influence from distant nodes. Information centrality measures a node's centrality within a network by considering the volume of information that flows through it.

The global variant of this metric calculates the harmonic mean of these distances, making it particularly effective in tracking information dissemination throughout the network. The insights derived from graph analysis techniques enable the identification of nodes with significant importance, prominence, strength, and prestige. The interpretation of these calculated nodes aligns with the information presented in the "comparison and overarching" table, as seen in Chart 1. This study aims to analyse the impact of digital transformation criteria on the various components of intellectual capital using directed edges and unilateral examination. Understanding dynamic capabilities, prominent characteristics, and nonlocal centrality metrics is greatly enriched by insights from existing scholarly literature. This study underscores its conceptual significance as a noteworthy and substantial contribution to the existing literature. It is a foundation for further exploring and understanding the intricate relationship between nonlocal centrality metrics, dynamic capabilities, and open innovation strategies. Incorporating this feature is expected to substantially impact the existing body of research, providing a valuable "comparison and overarching" chart. In addition to the substantial contributions made by this study, there are several promising avenues for future research in this domain. Some of the potential areas of focus include:

Application Across Industries: This study primarily delves into the context of open innovation and intellectual capital within organizations. Future research could explore the applicability of nonlocal centrality metrics in various industries and sectors, ranging from healthcare and finance to education and government.

Temporal Analysis: Understanding how nonlocal centrality metrics evolve can provide insights into the dynamic nature of networks. Future studies may investigate how these metrics change during innovation and transformation processes.

Comparative Analysis: Comparative analyses across diverse organizations and industries can reveal patterns and variations in the relationships between nonlocal centrality metrics, dynamic capabilities, and open innovation strategies.

Advanced Network Structures: As networks become more complex and interconnected, further research could explore how nonlocal centrality metrics adapt to advanced network structures, including multiplex networks, temporal networks, and dynamic networks.

Integration of Artificial Intelligence: With the growing role of artificial intelligence and machine learning in organizational decision-making, research could investigate how AI-driven insights can complement and enhance the utilization of nonlocal centrality metrics.

Practical Implementation: Future studies can explore how the findings and insights from this research can be practically implemented in real-world organizational strategies, aiding in optimizing innovation processes and intellectual capital management.

By focusing on these future research directions, scholars and practitioners can continue to expand our understanding of nonlocal centrality metrics and their implications for organizational strategies, dynamic capabilities, and open innovation initiatives. These inquiries hold the potential to drive innovation and competitiveness in an increasingly interconnected and data-driven world. It is essential to acknowledge the limitations of this study, as they provide valuable insights for future research and practical applications. Some of the limitations include:

Contextual Specificity: This study primarily focuses on the context of open innovation and intellectual capital within organizations. The findings may not be directly transferable to other contexts or industries, and additional research is needed to assess the generalizability of the results.

Data and Network Structure: The quality of network data and the specific structure of networks can significantly impact the application of nonlocal centrality metrics. Variations in data quality and network structures may yield different results.

Measurement Challenges: The accuracy of nonlocal centrality metrics is contingent on the completeness and accuracy of data used for analysis. Incomplete or biased data may lead to limitations in the metrics' effectiveness.

Dynamic Nature of Networks: Networks are dynamic, and the relationships among nodes can change over time. This study offers a static snapshot, and the dynamics of network changes may not be fully captured.

Interpretation Complexity: Interpreting nonlocal centrality metrics can be challenging, as their significance may vary based on the specific context and research question. Careful consideration is required for a meaningful interpretation.

Scope of Metrics: While this study covers several nonlocal centrality metrics, numerous other metrics and variations exist. The selection of metrics and their combination may influence the findings.

External Factors: External factors, such as market conditions, economic changes, or unforeseen events, can impact the effectiveness of open innovation strategies and intellectual capital. These external influences are not explicitly considered in this study.

Understanding these limitations is crucial for comprehensively interpreting the study's findings and guiding future research. Addressing these limitations in subsequent studies can lead to a more robust understanding of the relationships between nonlocal centrality metrics, dynamic capabilities, and open innovation strategies. In conclusion, nonlocal centrality measurements are invaluable tools for comprehending the structural and functional significance of nodes within a network. The choice of a specific metric depends on the research question, network attributes, and the particular facet of significance being investigated.

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