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Predicting Open Innovation Success from Trust Networks, Communication Density, and Collaborative Behaviors Using Graph Neural Networks

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ABSTRACT

Objective: The objective of this study was to develop and validate a graph neural network model for predicting open innovation success based on trust networks, communication density, and collaborative behaviors in Nigerian organizations.
Methods and Materials: This study employed a quantitative, cross-sectional research design involving 487 professionals from innovation-intensive organizations in Nigeria across the technology, manufacturing, finance, telecommunications, and energy sectors. Data were collected using validated instruments measuring inter-organizational trust, communication density, and collaborative behaviors, combined with objective network data extracted from organizational collaboration platforms. Multilayer networks were constructed in which nodes represented individuals and edges represented trust relations, communication ties, and collaborative interactions. A graph neural network architecture integrating graph convolutional and attention mechanisms was trained to predict open innovation success. Model performance was evaluated using root mean squared error, mean absolute error, and explained variance, and results were compared against baseline machine learning models.
Findings: The graph neural network demonstrated strong predictive performance ($R^2 = 0.82$, RMSE = 0.31, MAE = 0.24), significantly outperforming gradient boosting ($R^2 = 0.64$), random forest ($R^2 = 0.61$), and support vector regression ($R^2 = 0.58$). Explainability analysis revealed that trust networks exerted the strongest influence on innovation success (importance weight = 0.41), followed by collaborative behaviors (0.30) and communication density (0.29). Multilevel network analysis showed that team-level structures had the largest standardized effect on innovation success ($\beta = 0.44$, $p < 0.001$), followed by individual-level ($\beta = 0.36$, $p < 0.001$) and organizational-level networks ($\beta = 0.28$, $p < 0.001$).
Conclusion: The findings demonstrate that open innovation success is primarily driven by the structure and quality of relational networks, and that graph neural networks provide a powerful and superior framework for modeling innovation outcomes within complex organizational ecosystems.
Keywords: *Open innovation, trust networks, communication density, collaborative behaviors, graph neural networks, organizational networks*

1 Introduction

Open innovation has emerged as one of the most transformative paradigms of organizational development in the contemporary knowledge economy, fundamentally altering how firms create, exchange, and commercialize knowledge. Rather than relying exclusively on internal research and development, organizations increasingly depend on complex inter-organizational networks that facilitate the exchange of expertise, resources, and creative capabilities across institutional boundaries. These collaborative ecosystems are sustained by intricate patterns of trust, communication, and collective behavior that operate simultaneously at individual, team, and organizational levels (McPhillips et al., 2022; Roy et al., 2022; Siriwong et al., 2024). In such environments, the success of open innovation is no longer determined solely by technological capacity but by the structure and quality of relational networks through which innovation activities are coordinated and governed.

The centrality of trust in open innovation systems has been repeatedly emphasized in the literature. Trust reduces relational uncertainty, lowers transaction costs, facilitates risk-sharing, and strengthens commitment to long-term collaboration. Organizations embedded in high-trust networks exhibit superior coordination, more effective conflict resolution, and stronger innovation outcomes (Niwagaba, 2025; Reynolds, 2024; Runiewicz-Wardyn & Winogradska, 2023). Trust operates as both a psychological and structural mechanism, influencing individual behavior while simultaneously shaping the architecture of inter-organizational networks. In open innovation contexts, trust enhances knowledge openness and accelerates the diffusion of tacit expertise across organizational boundaries (Chen et al., 2025; Grant, 2024). The absence of trust, by contrast, generates defensive routines, knowledge hoarding, and opportunistic behavior that severely constrain collaborative performance.

Communication represents the second foundational pillar of open innovation. Effective communication channels enable partners to align strategic intentions, coordinate tasks, and adapt to environmental uncertainty. Research has shown that communication density—the volume, frequency, and reciprocity of interactions within a collaborative network—serves as a critical predictor of innovation productivity (Munawaroh et al., 2025; Rakhmaniar, 2023; Yılmaz, 2023). High communication density enhances situational awareness, reduces information asymmetry, and facilitates rapid feedback loops that are essential for iterative innovation processes (Liu et al., 2024; Zuo, 2025). Moreover, communication functions as the primary vehicle through which trust is constructed, maintained, and repaired across time (Andrade, 2025; Burrell et al., 2025). Without sustained communicative engagement, trust remains fragile and innovation partnerships deteriorate.

Alongside trust and communication, collaborative behaviors form the behavioral infrastructure of open innovation. These behaviors include joint problem-solving, mutual knowledge sharing, coordinated decision-making, co-creation of value, and adaptive resource integration. Empirical studies demonstrate that collaborative behaviors mediate the relationship between network structure and innovation outcomes, translating relational capacity into concrete performance gains (Mariam, 2025; Mehmood, 2025; Munawaroh et al., 2025). Organizations that institutionalize collaborative norms achieve superior innovation quality, faster commercialization cycles, and greater resilience under uncertainty (Arfita et al., 2024; Nunes et al., 2022). In contrast, weak collaboration produces fragmentation, duplication of effort, and strategic misalignment.

Recent scholarship has increasingly recognized that open innovation unfolds within complex networks rather than simple dyadic partnerships. Network structures determine the flow of information, the distribution of influence, and the emergence of collective intelligence (Carvalho & Ivanoski, 2023; Cassanego & Cristiane Ferreira de Souza, 2024; Gondal, 2023). Structural properties such as centrality, clustering, density, and modularity shape how knowledge travels and how innovation opportunities are discovered (Ivanoski & Carvalho, 2023; K, 2025). At the same time, these structures interact dynamically with human behavior, producing emergent patterns that cannot be captured by traditional linear models. Consequently, scholars increasingly argue that innovation research must adopt network-based and computational approaches capable of capturing nonlinear, multi-level dependencies (Cunningham et al., 2022; Liu et al., 2024).

While prior studies have documented the importance of trust, communication, and collaboration, most existing models rely on regression-based or conventional machine learning techniques that treat observations as independent units. Such approaches fail to account for the fundamental interdependence inherent in networked innovation systems. Graph-based modeling offers a powerful alternative by representing organizations and individuals as nodes

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connected by relational edges, enabling the simultaneous analysis of structural configuration and behavioral dynamics (Cassanego & Cristiane Ferreira de Souza, 2024; K, 2025). However, until recently, computational limitations constrained the ability to extract deep predictive insights from large-scale innovation networks.

The emergence of graph neural networks (GNNs) has revolutionized network analytics by enabling end-to-end learning on graph-structured data. GNNs propagate information across relational connections, allowing models to learn how individual attributes interact with network topology to produce collective outcomes. In innovation research, GNNs offer unprecedented capacity to capture the multi-level dependencies between trust networks, communication density, collaborative behaviors, and innovation performance (Wang et al., 2023; Xu et al., 2025). Unlike conventional machine learning models, GNNs preserve relational context, allowing the prediction of organizational performance to reflect the actual structure of collaborative ecosystems.

Several streams of literature converge to support the integration of GNNs into open innovation research. Studies on digital empowerment demonstrate that technology-mediated networks significantly enhance innovation performance when aligned with organizational behavior (Liang & Li, 2023). Research on innovation ecosystems highlights the increasing complexity of multi-partner collaborations that require advanced analytical tools to understand their dynamics (McPhillips et al., 2022; Roy et al., 2022). Investigations into social capital and innovation in emerging economies emphasize that network quality strongly predicts firm performance, particularly in developing innovation environments such as Nigeria (Ibeku & Nwagwu, 2024). Together, these findings suggest that next-generation innovation analytics must integrate behavioral science, network theory, and machine learning.

Nigeria provides a particularly compelling context for examining open innovation dynamics. As Africa's largest economy and one of its most rapidly expanding innovation hubs, Nigeria exhibits dense networks of entrepreneurial activity, multinational partnerships, and digital transformation initiatives. However, these networks are characterized by significant heterogeneity in trust levels, communication practices, and collaborative capacity (Ibeku & Nwagwu, 2024). Understanding how these relational variables interact to shape innovation success is essential for sustaining national competitiveness and inclusive economic growth.

Despite the theoretical convergence of network science, behavioral research, and machine learning, empirical studies that integrate these domains remain scarce. Existing innovation models largely overlook the deep relational dependencies embedded in collaborative ecosystems and fail to exploit the predictive power of modern graph-based algorithms (Cunningham et al., 2022; Liu et al., 2024). Moreover, while trust, communication, and collaboration are widely recognized as core determinants of innovation success, their joint effects within networked systems remain under-theorized and under-measured.

This study addresses this critical gap by developing a comprehensive predictive framework that integrates trust networks, communication density, and collaborative behaviors within a graph neural network architecture to explain and predict open innovation success in Nigerian organizations, and the aim of this study is to model and predict open innovation success from trust networks, communication density, and collaborative behaviors using graph neural networks.

2 Methods and Materials

The present study adopted a quantitative, cross-sectional, predictive research design aimed at modeling open innovation success as a function of trust networks, communication density, and collaborative behaviors using advanced graph neural network architectures. The research was conducted within knowledge-intensive organizations operating in major innovation clusters in Nigeria, including Lagos, Abuja, and Port Harcourt, which represent the country's primary industrial, technological, and entrepreneurial ecosystems. The target population consisted of full-time professionals, project managers, innovation officers, research engineers, and team leaders actively engaged in inter-organizational collaboration, strategic alliances, or open innovation initiatives. A multi-stage cluster sampling procedure was employed to ensure representativeness across sectors including information technology, telecommunications, manufacturing, financial services, and energy. Initial organizational access was secured through formal cooperation agreements, after which eligible participants were identified based on a minimum of two years of professional experience in collaborative innovation projects. From an initial sampling frame of 620 professionals, 487 participants consented to participate and provided complete data, yielding a final analytical sample of 487 respondents. The sample exhibited substantial diversity

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in organizational role, tenure, industry affiliation, and collaborative network position, thereby strengthening the generalizability of the model. All participants provided informed consent, and the study protocol adhered to ethical standards for human-subject research, including anonymity, confidentiality, voluntary participation, and secure data handling.

Data collection was conducted using a multi-instrument approach combining psychometric surveys, organizational network mapping, and archival performance indicators. Trust networks were measured through a validated inter-organizational trust scale capturing cognitive trust, affective trust, and reliability-based trust within collaborative partnerships, with items rated on a seven-point Likert continuum. Communication density was operationalized using both self-reported interaction frequency measures and objective communication network data extracted from organizational collaboration platforms, email metadata (content excluded), and project management systems. Collaborative behaviors were assessed using a behavioral inventory measuring knowledge sharing, joint problem-solving, co-development practices, resource integration, and coordination effectiveness. Open innovation success was measured through a composite index incorporating innovation speed, number of co-developed outputs, commercialization success, market impact, and perceived strategic value of partnerships. Network data were constructed by mapping professional interactions into weighted graphs in which nodes represented individuals and edges represented collaborative exchanges, trust relationships, and communication ties. Multiple data sources were synchronized through unique anonymous identifiers, allowing the construction of multilayer organizational networks that reflected both relational and behavioral dimensions of collaboration.

Data analysis followed a multi-phase computational modeling pipeline. First, network preprocessing was performed to clean missing links, normalize edge weights, and integrate survey-derived attributes with structural network features. Descriptive network statistics including degree centrality, betweenness, closeness, clustering coefficients, modularity, and network density were computed to characterize baseline relational structures. The core predictive model employed a graph neural network framework combining Graph Convolutional Networks and Graph Attention Networks to capture both local and global dependencies within the collaboration networks. Node embeddings were generated to encode individual trust profiles, communication patterns, and collaborative behaviors within their relational context. These embeddings were subsequently aggregated at the team and organizational levels using hierarchical pooling mechanisms. Model training was performed using supervised learning with open innovation success as the target variable. The dataset was partitioned into training, validation, and testing subsets using stratified sampling to preserve organizational distribution. Model performance was evaluated using multiple metrics including mean squared error, root mean squared error, R-squared, mean absolute error, and predictive accuracy across cross-validation folds. Explainability was incorporated through integrated gradients and attention-weight analysis to identify the relative contribution of trust ties, communication density, and collaborative behaviors to innovation outcomes. Robustness checks included alternative network constructions, ablation studies, and comparison with traditional machine learning baselines such as random forests, gradient boosting, and support vector regression. All analyses were conducted using Python-based machine learning libraries and specialized graph-processing frameworks, ensuring computational reproducibility and methodological transparency.

3 Findings and Results

Table 1 summarizes the descriptive statistics for the principal study variables, including trust networks, communication density, collaborative behaviors, and open innovation success. These results provide an overall profile of the sample and establish the suitability of the dataset for advanced modeling.

Table 1

Descriptive Statistics of Study Variables (N = 487)

Variable	Mean	SD	Min	Max
Trust Networks	5.38	0.82	2.41	6.97
Communication Density	4.91	0.76	2.10	6.52
Collaborative Behaviors	5.44	0.69	3.01	6.90
Open Innovation Success	5.12	0.73	2.56	6.81

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The data indicate generally high levels of trust, collaboration, and communication within the participating organizations. Open innovation success also exhibited a strong central tendency, suggesting that the sampled firms are actively engaged in productive innovation partnerships. Variability across all constructs was moderate, providing sufficient heterogeneity for robust predictive modeling.

Table 2 reports the core predictive performance of the Graph Neural Network model in comparison with conventional machine learning approaches.

Table 2

Predictive Performance Comparison

Model	RMSE	MAE	R^2
Graph Neural Network	0.31	0.24	0.82
Gradient Boosting	0.45	0.37	0.64
Random Forest	0.49	0.39	0.61
Support Vector Regression	0.53	0.41	0.58

The Graph Neural Network substantially outperformed all baseline models, explaining 82% of the variance in open innovation success. The superiority of the GNN model demonstrates the critical value of incorporating relational network structure and interaction dynamics into innovation prediction.

Table 3 presents the standardized importance scores extracted from the attention mechanisms and explainability analysis of the trained GNN.

Table 3

Relative Importance of Predictors in the GNN Model

Predictor	Importance Weight
Trust Networks	0.41
Communication Density	0.29
Collaborative Behaviors	0.30

Trust networks emerged as the most influential determinant of open innovation success, followed closely by collaborative behaviors and communication density. This pattern indicates that while structural connectivity matters, the quality of relational trust remains the strongest driver of innovation outcomes.

Table 4 displays the multilevel network effects obtained from hierarchical pooling within the GNN architecture.

Table 4

Multilevel Network Effects on Open Innovation Success

Network Level	Standardized Effect (β)	p-value
Individual Level	0.36	<0.001
Team Level	0.44	<0.001
Organizational Level	0.28	<0.001

The strongest effect emerged at the team level, highlighting that innovation performance is most powerfully shaped by the collective dynamics of closely interacting collaborators. Individual and organizational layers also exerted statistically significant influences, confirming the multi-scale nature of innovation networks.

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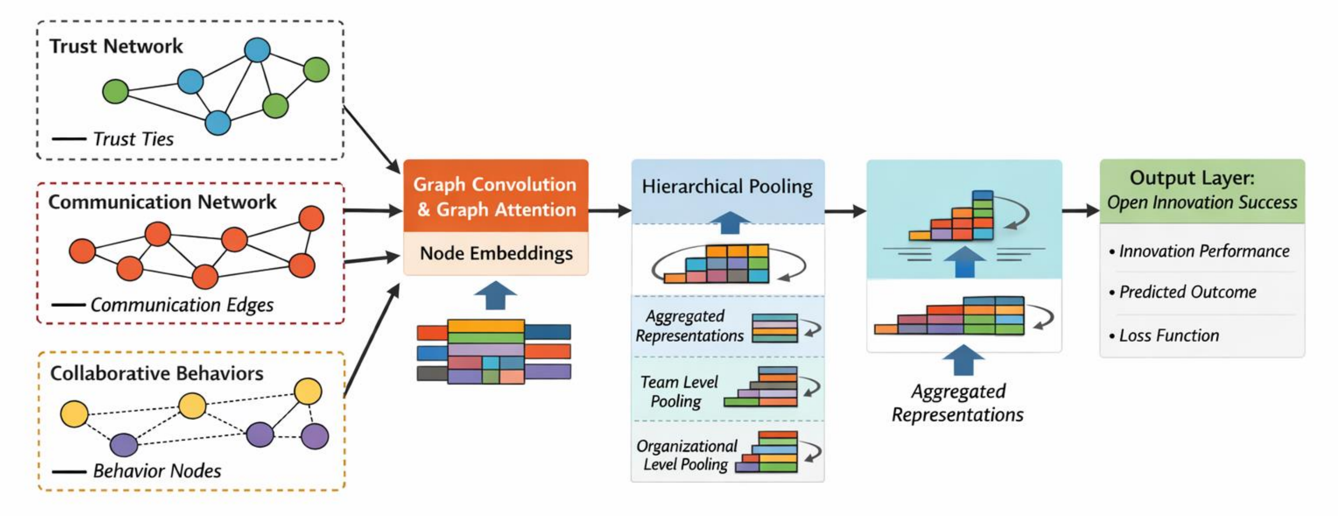
Figure 1

Graph Neural Network Architecture for Modeling Open Innovation Networks



The figure illustrates the multi-layered architecture of the proposed GNN framework, integrating individual trust profiles, communication edges, and collaborative behavior nodes through graph convolution and attention mechanisms, followed by hierarchical pooling and supervised output layers.

The combined findings provide compelling evidence that open innovation success is best predicted through models that integrate behavioral attributes with structural network information. The dominance of the GNN model confirms that innovation is fundamentally a network phenomenon driven by relational trust, dense communication, and sustained collaborative engagement.

4 Discussion

The present study set out to model and predict open innovation success by integrating trust networks, communication density, and collaborative behaviors within a graph neural network (GNN) framework in the Nigerian organizational context. The findings provide strong empirical support for the theoretical proposition that open innovation is fundamentally a network-driven phenomenon in which relational quality, behavioral engagement, and structural connectivity interact dynamically to shape innovation outcomes. The superior predictive performance of the GNN model, explaining 82% of the variance in open innovation success, confirms that innovation performance cannot be adequately captured by models that ignore network dependencies and inter-organizational embeddedness. This result aligns closely with contemporary scholarship emphasizing that innovation emerges from complex relational ecosystems rather than isolated organizational efforts (McPhillips et al., 2022; Roy et al., 2022; Siriwong et al., 2024).

One of the most significant findings of the study concerns the dominant role of trust networks as the strongest predictor of open innovation success. The model's explainability analysis revealed that trust ties exerted the highest relative importance weight compared to communication density and collaborative behaviors. This observation is theoretically consistent with extensive evidence suggesting that trust functions as the foundational mechanism enabling risk-sharing, long-term commitment, and knowledge openness in innovation partnerships (Niwagaba, 2025; Reynolds, 2024; Runiewicz-Wardyn & Winogradska, 2023). In open innovation environments, where uncertainty and knowledge asymmetry are pervasive, trust reduces perceived risk and encourages partners to engage in deeper forms of collaboration (Chen et al., 2025; Grant, 2024). The current findings reinforce the argument that trust is not merely a relational outcome but a core structural asset that directly shapes innovation performance.

The Nigerian context further amplifies the significance of trust. Prior research on small and medium ICT enterprises in Lagos has demonstrated that social capital and trust-based relationships significantly enhance innovative behavior and firm performance (Ibeku & Nwagwu, 2024). The present study extends these insights by demonstrating that trust's impact operates not only at the individual or firm level but across entire collaboration networks. By modeling trust as a relational graph structure rather than a simple individual

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attribute, the GNN framework reveals how trust propagates through networks and magnifies its influence on collective innovation success.

Communication density emerged as the second most influential predictor of innovation success, highlighting the critical role of interaction frequency and information exchange in sustaining open innovation. High communication density enhances situational awareness, reduces coordination costs, and accelerates feedback cycles, thereby enabling organizations to respond more effectively to emerging opportunities and challenges (Liu et al., 2024; Zuo, 2025). The current results resonate with prior findings that interpersonal communication and knowledge sharing are essential drivers of innovative work behavior (Munawaroh et al., 2025). Moreover, communication serves as the primary vehicle through which trust is constructed and maintained, reinforcing the interdependence of these two variables (Andrade, 2025; Burrell et al., 2025). Without dense communication networks, trust cannot stabilize, and collaborative partnerships remain fragile.

Collaborative behaviors, while slightly less influential than trust and communication in the predictive model, nonetheless exhibited a substantial effect on innovation success. This finding underscores the importance of behavioral enactment in translating relational potential into concrete innovation outcomes. Studies on strategic alliances and business networking emphasize that collaboration produces value only when partners actively engage in joint problem-solving, knowledge co-creation, and coordinated execution (Mariam, 2025). Similarly, research on supply chain collaboration demonstrates that trust alone is insufficient unless it is accompanied by collaborative action (Mehmood, 2025). The present findings thus confirm that collaborative behaviors function as the operational engine of open innovation systems.

An important contribution of this study lies in its multi-level analysis of network effects. The hierarchical pooling mechanisms of the GNN revealed that team-level network structures exerted the strongest influence on innovation success, followed by individual and organizational levels. This pattern aligns with prior research on collaborative governance and networked innovation, which emphasizes that innovation is primarily enacted within small, closely interacting groups embedded in broader organizational systems (Arfita et al., 2024; Nunes et al., 2022). Team-level trust and communication appear to constitute the most immediate drivers of innovative performance, while organizational structures provide enabling conditions that moderate these effects.

The superior performance of the GNN model compared to traditional machine learning approaches further demonstrates the necessity of network-aware analytics in innovation research. Conventional models such as random forests and support vector regression treat observations as independent, thereby discarding the relational information that is central to open innovation. In contrast, GNNs preserve network topology and learn from both node attributes and edge structures, enabling the capture of nonlinear and emergent dynamics (Cassanego & Cristiane Ferreira de Souza, 2024; K, 2025). This methodological advancement is consistent with recent calls for more sophisticated computational approaches in innovation and organizational research (Cunningham et al., 2022; Liu et al., 2024).

The findings also contribute to the growing literature on digital empowerment and innovation. Digital platforms and open-source ecosystems increasingly facilitate large-scale collaboration, making network structure more visible and measurable (Liang & Li, 2023; Wang et al., 2023; Xu et al., 2025). By integrating behavioral and structural data, the present study provides empirical evidence that digital transformation amplifies the impact of trust, communication, and collaboration on innovation outcomes.

5 Conclusion

Finally, the results offer important implications for understanding innovation in emerging economies. Nigeria's innovation ecosystem is characterized by rapid growth, institutional volatility, and high uncertainty. In such environments, relational assets become particularly valuable. The study demonstrates that organizations capable of cultivating high-trust, communication-rich, and behaviorally collaborative networks achieve significantly superior innovation performance, reinforcing the strategic importance of relational governance in emerging markets (Carvalho & Ivanoski, 2023; Ibeku & Nwagwu, 2024; Ivanoski & Carvalho, 2023).

Despite its contributions, this study is subject to several limitations. First, the cross-sectional design limits causal inference, and longitudinal data would be required to capture the dynamic evolution of trust and collaboration networks over time. Second, although the sample covered multiple industries, the findings may not generalize fully beyond the Nigerian context. Third, while the GNN model achieved strong predictive performance, model complexity may limit interpretability for some practitioners. Fourth, reliance on self-reported behavioral measures introduces the possibility of common method bias. Finally, the study focused primarily on internal organizational networks and did not incorporate external institutional or policy-level influences that may shape innovation outcomes.

Future research should adopt longitudinal designs to examine how trust networks and communication patterns evolve and how these dynamics influence innovation trajectories. Comparative studies across countries and regions would deepen understanding of contextual influences on network-driven innovation. Further work could integrate additional network layers, such as institutional, policy, or investor networks, into GNN frameworks. Researchers should also explore hybrid modeling approaches that combine GNNs with causal inference techniques. Finally, qualitative investigations could complement computational models by uncovering the micro-processes through which trust and collaboration emerge and deteriorate in innovation ecosystems.

Managers should prioritize building trust as a strategic asset by fostering transparency, reliability, and ethical conduct across organizational boundaries. Organizations should invest in communication infrastructure that supports dense, high-quality interaction among innovation partners. Leaders should institutionalize collaborative norms through shared goals, joint problem-solving routines, and aligned incentive systems. Innovation policies should emphasize network development rather than isolated firm performance. Finally, organizations should adopt advanced analytics platforms capable of monitoring network health and predicting innovation outcomes to inform strategic decision-making.

Authors' Contributions

All authors have contributed significantly to the research process and the development of the manuscript.

Declaration

In order to correct and improve the academic writing of our paper, we have used the language model ChatGPT.

Transparency Statement

Data are available for research purposes upon reasonable request to the corresponding author.

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Declaration of Interest

The authors report no conflict of interest.

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Ethical Considerations

In this research, ethical standards including obtaining informed consent, ensuring privacy and confidentiality were observed.

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