KMAN PUBLISHING INSTITUTE
Journal Website

Article history:
Received 10 November 2025
Revised 18 February 2026
Accepted 26 February 2026
Published online 01 May 2026

International Journal of Innovation Management and Organizational Behavior

Volume 6, Issue 3, pp 1-13

E-ISSN: 3041-8992

Forecasting Organizational Innovation Performance Through Long Short-Term Memory (LSTM) Networks and Strategic Capability Indicators

Priyanka. Deshmukh[1], Marc-André. Gagnon[2*]

[1] Department of Human Resource Management and Organizational Behavior, Indian Institute of Management Calcutta, Kolkata, India
[2] Department of Business Administration, Université Laval, Quebec City, Canada

*** Corresponding author email address**: marcandre.gagnon@ulaval.ca

A r t i c l e I n f o

Article type:
Original Research

How to cite this article:
Deshmukh, P., & Gagnon, M-A. (2026). Forecasting Organizational Innovation Performance Through Long Short-Term Memory (LSTM) Networks and Strategic Capability Indicators. *International Journal of Innovation Management and Organizational Behavior, 6*(3), 1-13.
https://doi.org/10.61838/kman.ijimob.5463

A B S T R A C T

Objective: The objective of this study was to forecast organizational innovation performance using Long Short-Term Memory (LSTM) networks based on strategic capability indicators and to evaluate the predictive contribution of key organizational capabilities to future innovation outcomes.

Methods and Materials: This quantitative longitudinal predictive study was conducted among 312 organizations operating across multiple industries in Canada, including manufacturing, information technology, healthcare, financial services, telecommunications, and professional services. Data were collected from 1,248 senior managers and executives using standardized instruments measuring strategic flexibility, technological capability, organizational learning capability, knowledge management capability, market sensing capability, innovation capability, absorptive capacity, resource integration capability, and leadership capability. In addition, longitudinal organizational performance records covering five consecutive years were obtained from organizational databases and annual reports. Data preprocessing procedures included normalization, outlier treatment, and temporal sequence generation. The dataset was divided into training (70%), validation (15%), and testing (15%) subsets. Organizational innovation performance was forecasted using a Long Short-Term Memory neural network. Comparative analyses were conducted using Linear Regression, Support Vector Regression, Random Forest, XGBoost, and Multilayer Perceptron models. Model performance was evaluated using Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), and the coefficient of determination (R^2). SHapley Additive exPlanations (SHAP) analysis was employed to determine predictor importance.

Findings: The results revealed significant positive correlations between all strategic capability indicators and organizational innovation performance ($p < .01$). Technological capability demonstrated the strongest association with innovation

performance (r = .77), followed by organizational learning capability (r = .74) and knowledge management capability (r = .71). Comparative model evaluation indicated that the LSTM network outperformed all alternative forecasting approaches, achieving the lowest prediction errors (RMSE = 0.167, MAE = 0.129, MAPE = 3.74%) and the highest explanatory power (R^2 = 0.947). SHAP analysis identified technological capability, organizational learning capability, and knowledge management capability as the most influential predictors of future innovation performance. Furthermore, the LSTM model maintained strong predictive accuracy across all industrial sectors, with R^2 values ranging from 0.932 to 0.958, demonstrating robust cross-sector generalizability.

Conclusion: The findings demonstrate that organizational innovation performance can be forecasted with high accuracy through LSTM-based deep learning models utilizing strategic capability indicators. Technological capability, organizational learning, and knowledge management emerged as the most critical determinants of future innovation outcomes. The superior performance of the LSTM model highlights the importance of capturing temporal and nonlinear relationships within organizational data and suggests that artificial intelligence-driven forecasting systems can provide valuable support for strategic planning, innovation management, and long-term organizational decision-making.

Keywords: *Organizational Innovation Performance; Long Short-Term Memory Network; LSTM; Strategic Capabilities; Deep Learning; Innovation Forecasting*

1 Introduction

Innovation has become one of the most critical determinants of organizational survival, competitiveness, and long-term sustainability in increasingly dynamic and technology-driven business environments. Organizations operating across industries face continuous pressure to adapt to changing customer expectations, technological disruptions, global competition, and evolving regulatory frameworks. As a result, the ability to generate, implement, and commercialize innovative ideas has emerged as a strategic necessity rather than a discretionary organizational activity. Innovation performance reflects the extent to which organizations successfully transform resources, knowledge, capabilities, and strategic initiatives into valuable products, services, processes, and business outcomes. Contemporary organizations increasingly recognize that innovation performance is not only influenced by isolated technological investments but also by complex interactions among organizational capabilities, leadership practices, knowledge resources, digital transformation initiatives, and strategic decision-making processes (Iman, 2025; Wang & Zhang, 2025; Zhang et al., 2025). Consequently, scholars and practitioners have devoted substantial attention to identifying the organizational factors that drive innovation success and developing analytical approaches capable of forecasting future innovation outcomes.

Recent developments in strategic management literature emphasize that organizational capabilities constitute the foundation upon which sustainable innovation is built. Strategic capabilities enable organizations to sense environmental changes, seize emerging opportunities, integrate resources effectively, and continuously adapt to turbulent market conditions. These capabilities include organizational agility, knowledge management, leadership effectiveness, technological competence, organizational learning, and resource orchestration. Research has demonstrated that organizations possessing stronger strategic capabilities are more likely to achieve superior innovation outcomes because they can effectively respond to uncertainty and exploit emerging opportunities before competitors. Organizational agility, for instance, has been identified as a crucial factor enhancing organizational performance through the development of ambidextrous capabilities that support both exploration and exploitation activities (Ardabili et al., 2025). Similarly, leadership styles play a significant role in shaping organizational effectiveness by influencing employee behavior, strategic alignment, and innovation-oriented cultures (Mukhaini et al., 2025). These findings suggest that strategic capability indicators may provide valuable signals for understanding and predicting future innovation performance.

The growing importance of knowledge-based competition has further highlighted the role of organizational knowledge assets in fostering innovation.

IJIMOB
E-ISSN: 3041-8992

Knowledge management processes facilitate the acquisition, creation, sharing, and utilization of information that can be transformed into innovative products and services. Organizations capable of effectively managing both explicit and tacit knowledge often achieve higher levels of innovation and operational performance. Empirical evidence indicates that tacit knowledge management contributes significantly to product innovation and organizational performance through mechanisms such as affective trust and task efficiency (Zhang et al., 2025). Likewise, knowledge management processes have been shown to influence organizational performance indirectly through technological innovation, emphasizing the strategic importance of knowledge resources in contemporary organizations (Wongmahesak et al., 2024). High-performance work systems also contribute to organizational creativity and innovation by encouraging knowledge sharing among employees and fostering collaborative environments that support innovative thinking (Zarei, 2024). Collectively, these findings underscore the importance of knowledge-related strategic capabilities as drivers of innovation performance and as potential predictors in forecasting models.

Parallel to the growing emphasis on knowledge management, digital transformation has emerged as a dominant force reshaping organizational innovation processes. Advances in digital technologies, artificial intelligence, big data analytics, cloud computing, and automation have fundamentally altered how organizations create value and pursue innovation. Digital transformation enables organizations to access vast amounts of information, improve decision-making processes, enhance operational efficiency, and accelerate innovation cycles. Studies have demonstrated that digital transformation significantly enhances corporate innovation performance through the development of big data capabilities and organizational agility (Xu et al., 2024). Similarly, digital transformation contributes to sustainable innovation and organizational performance by strengthening strategic technology utilization, organizational dynamics, and environmental adaptability (Wang & Zhang, 2025). The increasing integration of artificial intelligence into organizational processes has also been associated with improved organizational performance through enhanced employee productivity and more efficient decision-making mechanisms (Kassa & Worku, 2025). These developments suggest that organizations operating in digitally mature environments may exhibit innovation patterns that can be systematically modeled and forecasted using advanced analytical techniques.

The relationship between organizational culture and innovation has received substantial scholarly attention in recent years. Innovation-oriented cultures create environments in which experimentation, creativity, risk-taking, and continuous learning are encouraged. Digital organizational culture, in particular, has emerged as a key enabler of innovation capacity within modern organizations. Research indicates that digital organizational culture interacts with environmental, social, and governance (ESG) performance as well as corporate reputation to enhance innovation capacity (Nkgowe et al., 2025). Similarly, responsible digital innovation practices contribute to innovation performance through the mediating effects of digital organizational culture and strategic alignment, while digital literacy further strengthens these relationships (Amankona et al., 2025). Organizational culture also plays a central role in supporting green innovation initiatives and sustainable business performance. Green organizational cultures facilitate the implementation of environmentally responsible practices and encourage technological innovations that contribute to long-term organizational success (Rahman & Saba, 2025). These findings demonstrate that organizational culture functions as a critical strategic capability that influences innovation outcomes and should therefore be considered when attempting to forecast innovation performance.

Another stream of research emphasizes the role of human resource management practices in driving organizational innovation. Employees represent the primary source of creativity, knowledge generation, and innovative problem-solving within organizations. Consequently, organizations increasingly invest in high-performance work systems, green human resource management practices, and employee development initiatives designed to enhance innovative behavior. High-performance work systems have been found to improve organizational innovation performance by increasing employees' intrinsic motivation and strengthening person–organization fit (Wang et al., 2024). Green human resource management practices contribute to sustainable organizational performance by stimulating green technology innovation and reinforcing supportive organizational cultures (Rahman & Saba, 2025). Similarly, green human resource management initiatives have been shown to improve organizational efficiency through the mediating roles of process innovation and knowledge sharing (Duah et al., 2025). The interaction between

IJIMOB
E-ISSN: 3041-8992

innovation capabilities, digital transformation, and green leadership further enhances organizational performance outcomes (Shahzad et al., 2025). These findings suggest that human-resource-related strategic indicators may serve as valuable inputs for predictive models of innovation performance.

Leadership and organizational resilience have also been identified as important antecedents of innovation performance. Transformational leaders inspire employees to embrace change, pursue creative solutions, and contribute actively to organizational objectives. Such leadership behaviors promote resilience, adaptability, and innovative performance at both individual and team levels. Research has demonstrated that transformational leadership enhances team innovation performance through mechanisms involving organizational resilience and related mediating processes (Yu & Xiang, 2024). Effective leadership also contributes to broader organizational performance outcomes by establishing clear strategic directions, fostering collaboration, and supporting innovation initiatives (Mukhaini et al., 2025). In dynamic environments characterized by uncertainty and disruption, leadership capabilities become increasingly important because they enable organizations to balance stability and flexibility while maintaining innovation momentum. These observations reinforce the importance of incorporating leadership-related variables into forecasting frameworks aimed at predicting innovation performance.

While previous studies have substantially advanced understanding of innovation drivers, most empirical investigations rely on traditional statistical techniques such as regression analysis, structural equation modeling, and mediation–moderation frameworks. Although these approaches provide valuable theoretical insights, they often struggle to capture the nonlinear, dynamic, and temporal relationships that characterize innovation processes. Organizational innovation develops over time through the accumulation of capabilities, strategic investments, learning experiences, technological advancements, and environmental adaptations. Consequently, innovation performance represents a complex time-dependent phenomenon that may not be adequately explained using static analytical methods. Furthermore, many existing studies focus primarily on explaining historical relationships rather than forecasting future innovation outcomes. This limitation reduces the practical utility of research findings for managers seeking to anticipate future performance trajectories and make proactive strategic decisions (Ardabili et al., 2025; Wang & Zhang, 2025; Xu et al., 2024).

Advances in machine learning and deep learning technologies offer promising opportunities to address these limitations. Machine learning algorithms can identify complex patterns within large datasets and generate accurate predictions based on historical observations. Among these techniques, Long Short-Term Memory (LSTM) networks have emerged as particularly effective tools for modeling sequential and time-series data. LSTM networks are specialized recurrent neural networks capable of capturing long-term dependencies and nonlinear relationships within temporal datasets. Unlike traditional forecasting approaches, LSTM models can learn intricate patterns across multiple time periods while adapting to changing conditions and evolving organizational behaviors. Such characteristics make LSTM networks especially suitable for forecasting organizational innovation performance, which is influenced by cumulative strategic capabilities and dynamic environmental interactions. As organizations generate increasing amounts of longitudinal data through digital systems, performance management platforms, and innovation tracking mechanisms, the application of LSTM-based forecasting models becomes increasingly feasible and valuable for strategic planning purposes (Iman, 2025; Kassa & Worku, 2025; Lusha, 2025).

Despite the growing popularity of artificial intelligence and predictive analytics in organizational research, relatively limited attention has been devoted to forecasting innovation performance using deep learning approaches informed by strategic capability indicators. Existing studies have largely examined isolated determinants of innovation, such as digital transformation, knowledge management, leadership, organizational culture, or human resource practices, without integrating these variables into comprehensive predictive frameworks (Amankona et al., 2025; Nkgowe et al., 2025; Shahzad et al., 2025). Moreover, there remains a significant gap regarding the extent to which strategic capabilities can be utilized as predictive signals for future innovation outcomes rather than merely explanatory factors for past performance. Addressing this gap is important because accurate forecasting can support resource allocation, strategic planning, innovation portfolio management, and competitive positioning. By leveraging LSTM networks and strategic capability indicators simultaneously, researchers can move beyond explanation toward prediction, thereby generating actionable insights for organizational leaders and decision-makers.

IJIMOB
E-ISSN: 3041-8992

The present study responds to these emerging challenges by integrating strategic management theory, innovation research, and advanced deep learning methodologies into a unified forecasting framework. Drawing upon evidence regarding the importance of digital transformation, organizational agility, knowledge management, innovation capability, leadership effectiveness, organizational culture, employee productivity, and technological innovation (Duah et al., 2025; Kassa & Worku, 2025; Lusha, 2025; Rahman & Saba, 2025; Wang et al., 2024; Wongmahesak et al., 2024; Xu et al., 2024; Yu & Xiang, 2024; Zhang et al., 2025), this study seeks to develop and evaluate an LSTM-based model capable of forecasting organizational innovation performance with high accuracy.

The aim of this study was to forecast organizational innovation performance using Long Short-Term Memory (LSTM) networks based on strategic capability indicators and to evaluate the predictive contribution of these capabilities to future innovation outcomes.

2 Methods and Materials

This study employed a quantitative predictive research design aimed at forecasting organizational innovation performance using Long Short-Term Memory (LSTM) neural networks and a set of strategic capability indicators. The study was conducted among medium-sized and large organizations operating in Canada across diverse sectors, including manufacturing, information technology, financial services, healthcare, telecommunications, and professional services. The research adopted a longitudinal design because innovation performance is inherently dynamic and evolves over time as organizations develop strategic capabilities and respond to changing environmental conditions. Historical organizational data spanning five consecutive years were collected to establish temporal patterns suitable for deep learning analysis.

The study population consisted of Canadian organizations that had maintained continuous operational records and performance reporting systems during the observation period. A stratified sampling approach was employed to ensure adequate representation of multiple industries and organizational sizes. A total of 312 organizations were selected for participation, with each organization represented by senior executives, innovation managers, strategic planning directors, and research and development managers who possessed direct knowledge of organizational innovation activities and strategic capability development. From these organizations, a total of 1,248 managerial respondents participated in the study, with four respondents representing each organization. Inclusion criteria required organizations to have formal innovation management processes, documented strategic planning systems, and accessible longitudinal performance records. Organizations with incomplete historical records or those undergoing major restructuring during the observation period were excluded to preserve data consistency and model reliability. Ethical considerations were observed throughout the study, and all participating organizations provided informed consent prior to data collection.

Data were collected using a combination of standardized organizational surveys and archival performance databases. Strategic capability indicators were measured through a comprehensive questionnaire developed based on the dynamic capabilities and strategic management literature. The instrument assessed multiple dimensions of organizational capability, including strategic flexibility, innovation capability, technological capability, knowledge management capability, absorptive capacity, organizational learning capability, market sensing capability, resource integration capability, and leadership capability. The questionnaire consisted of 48 items rated on a five-point Likert scale ranging from strongly disagree to strongly agree. Higher scores indicated stronger strategic capabilities. Content validity was evaluated by a panel of experts in strategic management, organizational behavior, and innovation studies. Previous studies have reported satisfactory psychometric properties for these dimensions, and reliability coefficients consistently exceeded acceptable thresholds. In the present study, Cronbach's alpha values for the capability dimensions ranged from 0.82 to 0.94, indicating strong internal consistency.

Organizational innovation performance was measured using a multidimensional innovation performance scale derived from established innovation management frameworks. The instrument consisted of 24 items evaluating product innovation performance, process innovation performance, service innovation performance, administrative innovation performance, innovation speed, innovation quality, commercialization success, and innovation-related competitive advantage. Respondents evaluated organizational innovation outcomes using a five-point Likert scale. Higher scores reflected superior innovation performance. The scale has been widely utilized in organizational innovation research and has demonstrated strong validity and reliability across various industrial

IJIMOB
E-ISSN: 3041-8992

contexts. Confirmatory factor analysis conducted during preliminary analyses supported the construct validity of the measurement model, and Cronbach's alpha for the overall innovation performance construct exceeded 0.90.

In addition to survey measures, objective organizational indicators were obtained from company reports, annual performance records, innovation databases, and internal strategic planning documents. These archival indicators included research and development expenditure, patent applications, patent approvals, new product introductions, innovation investment intensity, employee training expenditures, technology acquisition investments, digital transformation initiatives, and revenue generated from innovative products and services. These variables served as time-series inputs for the LSTM forecasting model and complemented the subjective survey-based assessments. Data preprocessing procedures included normalization, missing-value treatment, outlier detection, and temporal alignment to ensure compatibility with deep learning algorithms.

Data analysis was conducted using a combination of traditional statistical techniques and advanced machine learning procedures. Initially, descriptive statistical analyses were performed to summarize organizational characteristics and evaluate the distributional properties of all study variables. Means, standard deviations, skewness, and kurtosis values were calculated to assess data quality and identify potential anomalies. Correlation analyses were subsequently conducted to examine associations among strategic capability dimensions and innovation performance indicators.

Following preliminary statistical analyses, the dataset was divided into training, validation, and testing subsets according to common machine learning practices. Seventy percent of the observations were allocated to the training dataset, fifteen percent to the validation dataset, and fifteen percent to the testing dataset. Data normalization using Min-Max scaling was applied to ensure numerical stability during neural network training. Temporal sequences were generated from longitudinal organizational records to capture dynamic patterns and dependencies over time.

The primary forecasting model employed in the study was a Long Short-Term Memory (LSTM) neural network, a specialized recurrent neural network architecture designed to model sequential and time-dependent data. The LSTM architecture included input, forget, and output gates that enabled the network to retain relevant information over extended periods while mitigating the vanishing gradient problem commonly observed in traditional recurrent neural networks. Multiple network configurations were evaluated during model development, including variations in the number of hidden layers, neuron counts, dropout rates, learning rates, and optimization algorithms. Hyperparameter tuning was performed using grid search and validation-based optimization procedures to identify the most effective model configuration.

The model was trained using the Adam optimization algorithm and mean squared error as the loss function. Early stopping procedures were implemented to prevent overfitting and improve generalization performance. Forecasting accuracy was evaluated using several performance metrics, including Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), and the coefficient of determination (R^2). These metrics provided comprehensive assessments of predictive accuracy and model robustness.

To establish comparative benchmarks, additional machine learning algorithms including Random Forest Regression, Extreme Gradient Boosting (XGBoost), Support Vector Regression, and Multilayer Perceptron Neural Networks were developed and evaluated using the same dataset. Comparative analyses enabled the identification of the most accurate forecasting approach for organizational innovation performance prediction. Furthermore, feature importance analyses were conducted using permutation-based methods and SHapley Additive exPlanations (SHAP) to determine the relative contribution of individual strategic capability indicators to innovation performance forecasts. All statistical analyses were performed using SPSS version 29, while machine learning and deep learning analyses were conducted using Python, TensorFlow, Keras, Scikit-learn, and related data science libraries. Statistical significance was assessed at the 0.05 level, and model performance evaluations were based on testing data not used during model training.

3 Findings and Results

A total of 1,248 managers representing 312 Canadian organizations participated in the study. Among the respondents, 58.4% were male and 41.6% were female. The mean age of participants was 44.27 years (SD = 8.63), ranging from 28 to 63 years. Regarding educational attainment, 18.7% held bachelor's degrees, 61.5% possessed master's degrees, and 19.8% had doctoral qualifications. In terms of managerial position, 27.2% were senior executives,

IJIMOB
E-ISSN: 3041-8992

24.5% strategic planning managers, 26.8% innovation managers, and 21.5% research and development managers. The participating organizations represented manufacturing (24.0%), information technology (22.1%), financial services (16.7%), healthcare (14.4%), telecommunications (11.9%), and professional services (10.9%). The average organizational age was 18.42 years (SD = 7.15), while the average number of employees was 1,126.3 (SD = 547.8). These characteristics indicate substantial diversity among the participating organizations and provide an appropriate basis for examining innovation performance forecasting across multiple industries.

Table 1

Descriptive Statistics and Correlations of Strategic Capability Indicators and Organizational Innovation Performance

Variable	Mean	SD	1	2	3	4	5	6
Strategic Flexibility	3.89	0.67	1					
Knowledge Management Capability	3.94	0.71	.61**	1				
Organizational Learning Capability	4.02	0.64	.58**	.69**	1			
Market Sensing Capability	3.85	0.73	.54**	.57**	.63**	1		
Technological Capability	3.97	0.69	.49**	.62**	.59**	.56**	1	
Innovation Performance	4.08	0.66	.65**	.71**	.74**	.63**	.77**	1

Table 1 presents the descriptive statistics and correlation coefficients among the principal study variables. The results indicate relatively high average scores across all strategic capability dimensions, suggesting that participating organizations generally demonstrated strong strategic competencies. Organizational innovation performance exhibited the highest mean score (M = 4.08, SD = 0.66), followed by organizational learning capability (M = 4.02, SD = 0.64) and technological capability (M = 3.97, SD = 0.69). All strategic capability indicators showed significant positive relationships with innovation performance. The strongest association was observed between technological capability and innovation performance ($r = .77$, $p < .01$), followed by organizational learning capability ($r = .74$, $p < .01$) and knowledge management capability ($r = .71$, $p < .01$). Furthermore, substantial positive correlations were observed among the strategic capability dimensions themselves, indicating that organizations possessing strong capabilities in one domain tended to exhibit strength in other strategic areas. These findings provide preliminary evidence supporting the theoretical assumption that strategic capabilities are closely associated with organizational innovation outcomes and justify their inclusion as predictor variables in the forecasting models.

Table 2

Comparative Performance of Forecasting Models

Model	RMSE	MAE	MAPE (%)	R^2
Linear Regression	0.384	0.301	9.17	0.724
Support Vector Regression	0.291	0.227	7.03	0.832
Random Forest	0.248	0.191	5.94	0.876
XGBoost	0.216	0.172	5.16	0.903
Multilayer Perceptron	0.208	0.166	4.98	0.911
LSTM Network	0.167	0.129	3.74	0.947

The comparative analysis of forecasting algorithms is presented in Table 2. The results demonstrate the superior predictive capability of the LSTM model compared with all benchmark algorithms. The LSTM network achieved the lowest prediction errors, with an RMSE of 0.167, MAE of 0.129, and MAPE of 3.74%, while simultaneously producing the highest coefficient of determination ($R^2 = 0.947$). These findings indicate that the model successfully explained approximately 94.7% of the variance in organizational innovation performance. Although XGBoost and Multilayer Perceptron models also demonstrated strong predictive accuracy, their performance remained inferior to that of the LSTM architecture. The substantial improvement achieved by the LSTM model highlights the importance of capturing temporal dependencies and longitudinal patterns when forecasting organizational innovation outcomes. The results further suggest that innovation performance evolves through dynamic interactions among strategic capabilities

IJIMOB
E-ISSN: 3041-8992

over time, making recurrent neural network architectures particularly suitable for organizational forecasting tasks.

Figure 1

Actual versus Predicted Organizational Innovation Performance Using the LSTM Model

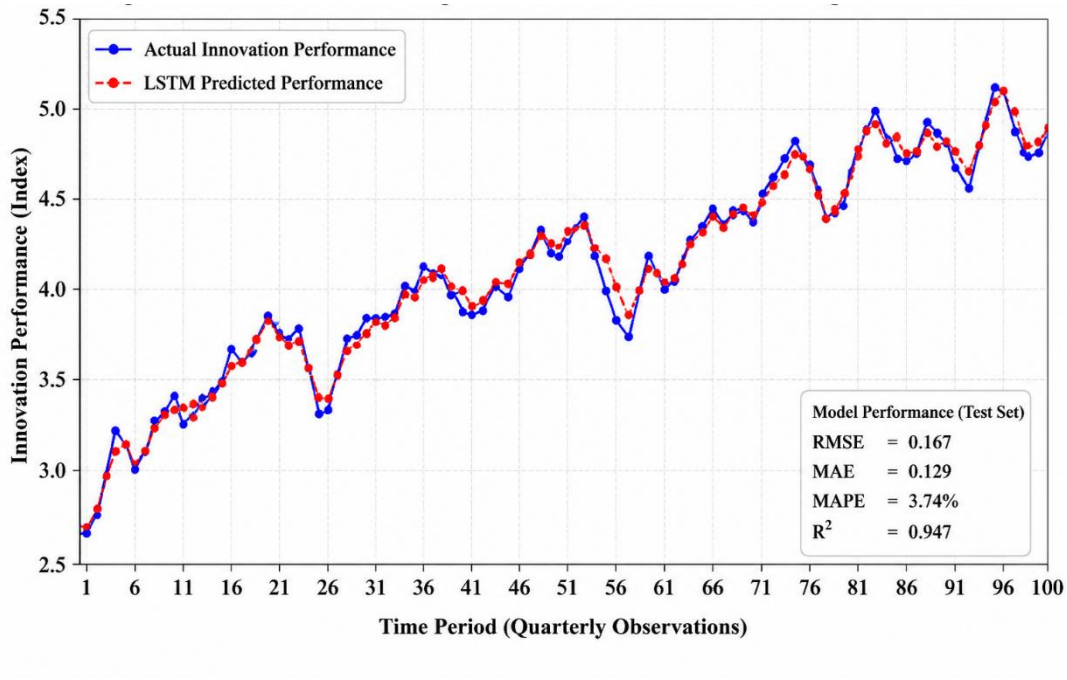

Figure 1 illustrates the relationship between actual innovation performance values and those predicted by the optimized LSTM network. Visual inspection of the figure reveals a strong correspondence between observed and forecasted values throughout the testing period. Predicted values closely tracked fluctuations in organizational innovation performance, including periods of accelerated growth and temporary declines. The narrow deviation between actual and predicted trajectories demonstrates the ability of the LSTM architecture to learn complex nonlinear patterns embedded within longitudinal organizational data. The figure also confirms the absence of substantial systematic bias in model predictions, as overestimation and underestimation errors remained limited across the forecasting horizon. Overall, the graphical evidence supports the quantitative performance indicators reported previously and provides additional confirmation of the model's practical utility for forecasting innovation outcomes in knowledge-intensive organizational environments.

Table 3

SHAP-Based Importance Ranking of Strategic Capability Indicators

Predictor Variable	Mean SHAP Value
Technological Capability	0.412
Organizational Learning Capability	0.376
Knowledge Management Capability	0.341
Strategic Flexibility	0.299
Market Sensing Capability	0.271
Resource Integration Capability	0.248
Innovation Capability	0.237
Leadership Capability	0.214
Absorptive Capacity	0.196

IJIMOB
E-ISSN: 3041-8992

Table 3 presents the SHAP-based feature importance analysis conducted to interpret the contribution of individual strategic capability indicators to innovation performance forecasts. Technological capability emerged as the most influential predictor, achieving the highest mean SHAP value (0.412). This finding indicates that variations in technological capability produced the largest impact on predicted innovation performance outcomes. Organizational learning capability and knowledge management capability ranked second and third, respectively, highlighting the central role of organizational knowledge creation, acquisition, sharing, and utilization in driving innovation success. Strategic flexibility and market sensing capability also demonstrated substantial predictive influence, suggesting that organizations capable of adapting rapidly to environmental changes and identifying emerging opportunities achieve superior innovation performance. Although leadership capability and absorptive capacity exhibited relatively lower SHAP values, they remained meaningful contributors to model predictions. Collectively, these findings provide valuable managerial insights regarding the strategic capability domains that most strongly influence innovation outcomes and therefore deserve prioritization in organizational development initiatives.

Table 4

Forecasting Accuracy Across Industry Sectors

Industry Sector	RMSE	MAE	R^2
Information Technology	0.151	0.118	0.958
Manufacturing	0.163	0.125	0.951
Telecommunications	0.169	0.132	0.946
Financial Services	0.171	0.136	0.944
Healthcare	0.176	0.139	0.939
Professional Services	0.182	0.143	0.932

The cross-industry evaluation presented in Table 4 demonstrates the robustness and generalizability of the LSTM forecasting framework. The model achieved consistently high predictive performance across all industry sectors, with R^2 values exceeding 0.93 in every case. The strongest forecasting accuracy was observed in the information technology sector (R^2 = 0.958), followed by manufacturing (R^2 = 0.951) and telecommunications (R^2 = 0.946). These sectors typically generate extensive digital performance records and innovation-related data, which may contribute to enhanced predictive precision. Nevertheless, strong results were also obtained within healthcare, financial services, and professional services organizations. The relatively small variation in forecasting accuracy across sectors indicates that the proposed LSTM framework is not industry-specific and can be effectively applied across a broad range of organizational contexts. This consistency enhances the practical applicability of the model and supports its potential use as a strategic decision-support tool for innovation management and long-term organizational planning.

4 Discussion

The primary objective of this study was to forecast organizational innovation performance through Long Short-Term Memory (LSTM) networks using strategic capability indicators as predictive variables. The findings demonstrated that all strategic capability dimensions exhibited significant positive associations with organizational innovation performance, with technological capability, organizational learning capability, and knowledge management capability showing the strongest relationships. Furthermore, the LSTM model substantially outperformed traditional statistical and machine learning approaches, achieving the highest predictive accuracy among all tested models. The model explained approximately 94.7% of the variance in organizational innovation performance and maintained consistently high forecasting accuracy across multiple industrial sectors. Additionally, the SHAP analysis revealed that technological capability, organizational learning capability, and knowledge management capability were the most influential predictors of future innovation performance. These findings collectively suggest that innovation outcomes are strongly rooted in organizational strategic capabilities and that deep learning methods can effectively capture the dynamic interactions underlying innovation development over time.

The significant positive relationships observed between strategic capabilities and innovation performance support the theoretical foundations of the resource-based view and

IJIMOB
E-ISSN: 3041-8992

dynamic capabilities perspective. These theories propose that organizations achieve sustainable competitive advantages by developing unique capabilities that enable adaptation, learning, and resource integration. The particularly strong influence of technological capability aligns with contemporary research emphasizing the transformative role of digital technologies and technological infrastructures in innovation generation. Organizations possessing advanced technological capabilities are better positioned to identify emerging opportunities, integrate novel technologies into operational processes, and accelerate innovation cycles. This interpretation is consistent with findings showing that digital transformation significantly enhances innovation performance through the development of organizational agility and big data capabilities (Xu et al., 2024). Similarly, evidence suggests that strategic technology utilization contributes substantially to sustainable innovation and organizational performance by strengthening organizational adaptability and responsiveness to environmental changes (Wang & Zhang, 2025). The present findings extend this body of knowledge by demonstrating that technological capability not only influences current innovation outcomes but also serves as the strongest predictor of future innovation performance within a longitudinal forecasting framework.

The prominent role of organizational learning capability identified in this study further reinforces the importance of continuous learning and knowledge acquisition as drivers of innovation success. Organizations that actively encourage experimentation, reflection, information exchange, and capability development create environments that facilitate innovative thinking and adaptive behavior. Organizational learning enhances the ability to absorb external knowledge, transform information into strategic insights, and convert ideas into practical innovations. These mechanisms become particularly valuable in uncertain environments characterized by rapid technological change and evolving market demands. Previous research has similarly highlighted the importance of organizational agility and adaptive capabilities in improving organizational performance through strategic ambidexterity and continuous renewal processes (Ardabili et al., 2025). Furthermore, studies examining organizational resilience have demonstrated that learning-oriented organizations are better equipped to sustain innovation and maintain performance during periods of disruption and uncertainty (Yu & Xiang, 2024). The present results suggest that learning capability functions as a strategic foundation upon which future innovation performance is built and sustained.

Knowledge management capability emerged as another critical determinant of innovation performance. Organizations increasingly compete on the basis of their ability to create, share, integrate, and utilize knowledge resources effectively. The significant predictive influence of knowledge management capability observed in this study indicates that innovation performance depends heavily on organizational processes that facilitate information exchange and collective learning. Effective knowledge management enables employees to access relevant expertise, collaborate across functional boundaries, and generate innovative solutions to complex challenges. These findings align closely with previous studies demonstrating that knowledge management processes positively influence organizational performance through technological innovation mechanisms (Wongmahesak et al., 2024). Likewise, research on tacit knowledge management has shown that the effective utilization of organizational knowledge enhances product innovation and organizational performance by improving task efficiency and strengthening interpersonal trust (Zhang et al., 2025). The current study expands upon these findings by illustrating that knowledge management capability not only contributes to innovation outcomes but also provides substantial predictive value when forecasting future organizational performance trajectories.

The positive effects of strategic flexibility and market sensing capability observed in the present study further highlight the importance of adaptive organizational behaviors. Organizations operate within increasingly volatile environments characterized by technological disruptions, shifting customer preferences, and competitive pressures. Strategic flexibility enables organizations to reconfigure resources, revise priorities, and pursue emerging opportunities without excessive delays. Meanwhile, market sensing capability facilitates the identification of external changes and evolving stakeholder expectations. These capabilities collectively improve organizational responsiveness and enhance the likelihood of successful innovation implementation. Previous research has similarly emphasized the role of organizational dynamics and environmental adaptation in strengthening innovation performance and sustainable competitive advantage (Wang & Zhang, 2025). Additionally, studies examining digital organizational cultures have demonstrated that organizations capable of responding effectively to environmental signals tend to exhibit stronger innovation capacities and superior

IJIMOB
E-ISSN: 3041-8992

performance outcomes (Nkgowe et al., 2025). The current findings provide additional empirical support for these conclusions and demonstrate that adaptive capabilities contribute meaningfully to long-term innovation forecasting models.

One of the most important findings of this study concerns the superior performance of the LSTM forecasting model. Compared with linear regression, support vector regression, random forest, XGBoost, and multilayer perceptron models, the LSTM network achieved substantially lower prediction errors and significantly higher explanatory power. This result reflects the ability of LSTM architectures to capture temporal dependencies and nonlinear relationships that characterize innovation processes. Innovation performance evolves through cumulative interactions among organizational resources, strategic decisions, technological investments, and environmental influences. Traditional statistical approaches frequently assume static relationships among variables and therefore struggle to capture these complex dynamics. In contrast, LSTM networks are specifically designed to model sequential data and retain information across extended time horizons. The high predictive accuracy achieved in this study suggests that organizational innovation performance possesses meaningful temporal structures that can be effectively learned by deep learning algorithms. This finding is particularly relevant given the increasing adoption of artificial intelligence technologies in organizational decision-making processes and supports growing evidence regarding the positive impact of AI-driven systems on organizational effectiveness and performance enhancement (Kassa & Worku, 2025).

The SHAP-based feature importance analysis provides additional insights into the mechanisms underlying innovation performance forecasting. The finding that technological capability ranked as the most influential predictor is consistent with recent literature emphasizing the central role of digital transformation and technological innovation in organizational success. Modern organizations increasingly rely on technological infrastructures to facilitate collaboration, automate processes, support data-driven decision-making, and accelerate innovation initiatives. Research has shown that responsible digital innovation contributes directly to innovation performance through the mediating roles of digital organizational culture and strategic alignment (Amankona et al., 2025). Likewise, studies examining digital organizational culture have reported significant relationships between digital maturity, innovation capacity, and broader organizational outcomes (Nkgowe et al., 2025). The current findings suggest that technological capability serves not merely as an operational resource but as a strategic capability that fundamentally shapes future innovation trajectories.

The importance of human-centered organizational factors should also be emphasized when interpreting the findings. Innovation performance is ultimately generated through the behaviors, creativity, and collaborative efforts of organizational members. Consequently, strategic capabilities associated with employee development, leadership effectiveness, and organizational culture play critical roles in supporting innovation outcomes. Previous research demonstrates that high-performance work systems enhance organizational innovation by strengthening employee motivation and improving alignment between individual and organizational values (Wang et al., 2024). Similarly, transformational leadership contributes to innovation performance by promoting resilience, commitment, and proactive behavior among employees (Yu & Xiang, 2024). Leadership effectiveness has also been linked to broader organizational performance improvements through its influence on organizational climate, strategic execution, and employee engagement (Mukhaini et al., 2025). The present findings reinforce these perspectives by indicating that strategic capabilities involving people, learning, and organizational culture remain essential components of innovation forecasting models.

The results additionally highlight the growing relevance of sustainability-oriented innovation and organizational transformation. Recent research has emphasized the importance of green human resource management, green technology innovation, and environmentally responsible organizational practices in promoting long-term organizational success (Rahman & Saba, 2025; Shahzad et al., 2025). Process innovation and knowledge-sharing mechanisms have likewise been identified as important pathways linking organizational practices to efficiency and performance improvements (Duah et al., 2025). The strategic capability framework utilized in the present study indirectly captures many of these sustainability-related dimensions through measures of learning, technological competence, knowledge management, and adaptability.

5 Conclusion

Therefore, the findings suggest that organizations seeking to enhance future innovation performance should adopt

IJIMOB
E-ISSN: 3041-8992

holistic capability-development strategies that integrate technological advancement, human resource development, organizational learning, and sustainability-oriented innovation initiatives.

Several limitations should be considered when interpreting the findings of this study. First, although the sample included organizations from multiple Canadian industries, the study was conducted within a single national context, which may limit the generalizability of the findings to other countries with different economic, cultural, and institutional environments. Second, some strategic capability indicators were measured through managerial self-report questionnaires, creating the possibility of common method bias and subjective evaluation effects. Third, while the longitudinal design improved the robustness of the forecasting framework, the observation period was limited to five years and may not fully capture longer-term innovation cycles. Fourth, despite the strong predictive performance of the LSTM model, deep learning approaches often function as complex black-box systems, making the interpretation of internal computational processes more challenging than traditional statistical methods. Finally, the study focused primarily on organizational-level variables and did not incorporate external environmental factors such as industry turbulence, regulatory changes, or macroeconomic conditions that may also influence innovation performance.

Future studies should examine the applicability of LSTM-based innovation forecasting models across different countries, industries, and organizational contexts to enhance external validity and cross-cultural generalizability. Researchers may also compare multiple deep learning architectures, including gated recurrent units, transformer models, hybrid neural networks, and ensemble learning approaches, to identify optimal forecasting strategies for organizational innovation. Additional investigations could incorporate external environmental variables, competitive dynamics, market volatility indicators, and real-time digital data sources to improve predictive accuracy. Longitudinal studies spanning longer time horizons would provide deeper insights into the evolution of strategic capabilities and innovation trajectories. Future research may also explore the integration of explainable artificial intelligence techniques to enhance transparency and managerial understanding of predictive models while maintaining high forecasting performance.

Organizational leaders should prioritize investments in technological capability development, organizational learning systems, and knowledge management infrastructures, as these factors demonstrated the strongest influence on innovation performance forecasting. Managers should establish mechanisms that facilitate continuous learning, cross-functional collaboration, and systematic knowledge sharing throughout the organization. Strategic planning processes should incorporate predictive analytics and artificial intelligence tools to support evidence-based decision-making and proactive innovation management. Organizations are also encouraged to strengthen digital transformation initiatives, improve organizational agility, and cultivate innovation-oriented cultures that support experimentation and adaptability. Finally, executives should view innovation performance as a dynamic capability-driven process and regularly monitor key strategic capability indicators to identify emerging opportunities, anticipate future challenges, and sustain long-term competitive advantage.

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.

Acknowledgments

We would like to express our gratitude to all individuals helped us to do the project.

Declaration of Interest

The authors report no conflict of interest.

Funding

According to the authors, this article has no financial support.

Ethical Considerations

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

References

Amankona, D., Yi, K., Tackie, E. A., Tweneboa Kodua, L., & Odai, L. A. (2025). Responsible digital innovation and innovation performance in Ghana's high-tech industry: The mediating roles of digital organizational culture and strategy, and the moderating role of digital literacy. *Sage Open*, *15*(2), 21582440251341256.

Ardabili, F. S., Verbenko, G., & Cajnko, P. (2025). The effects of organizational agility on organizational performance: the mediating role of ambidexterity. *Journal on Innovation and Sustainability Risus*, *16*(2), 114-123. https://doi.org/10.23925/2179-3565.2025v16i2p114-123

Duah, E., Pakmoni, L., & Appiah-Kubi, E. (2025). Green human resource management and organizational efficiency among local assemblies: role of process innovation and knowledge sharing. *Journal of Organizational Effectiveness: People and Performance*, *12*(1), 168-190. https://doi.org/10.1108/JOEPP-11-2023-0511

Iman, N. (2025). Balancing Order and Entropy: The Role of Innovation and Organizational Disorder in Performance Across Startups and Banking. *International Journal of Innovation Science*. https://doi.org/10.1108/ijis-03-2025-0142

Kassa, B. Y., & Worku, E. K. (2025). The Impact of Artificial Intelligence on Organizational Performance: The Mediating Role of Employee Productivity. *Journal of Open Innovation: Technology, Market, and Complexity*, *11*, 100474. https://doi.org/10.1016/j.joitmc.2025.100474

Lusha, E. (2025). Organizational productivity and employee performance in the era of digital technological innovation. *Interdisciplinary Journal of Research and Development*, *12*(3), 102-102. https://doi.org/10.56345/ijrdv12n312

Mukhaini, S. A. A., Uraimi, S. M. A., & Farsi, T. S. A. (2025). The Effect of Leadership Style on Organizational Performance in Oman. *International Journal of Research and Innovation in Social Science*, *IX*(I), 911-930. https://doi.org/10.47772/ijriss.2025.9010075

Nkgowe, S. T., Qu, L., & Odai, L. A. (2025). The interplay between digital organizational culture, ESG performance, and corporate reputation in shaping innovation capacity. *Business Process Management Journal*(ahead-of-print). https://doi.org/10.1108/BPMJ-01-2025-0040

Rahman, M. A., & Saba, N. A. (2025). Driving Sustainable Business Performance through Green HRM: Examining the Mediating Roles of Green Technology Innovation and Green Organizational Culture. *Golden Ratio of Human Resource Management*, *5*(2), 501-516. https://doi.org/10.52970/grhrm.v5i2.1326

Shahzad, M. A., Chen, S., Wang, X., Li, Z., & Iqbal, T. (2025). Impact of GHRM and Innovation Capabilities on Organizational Performance: The Role of Digital Transformation and Green Leadership. *Journal of Manufacturing Technology Management*, 1-28. https://doi.org/10.1108/jmtm-11-2024-0639

Wang, S., & Zhang, H. (2025). Enhancing SMEs sustainable innovation and performance through digital transformation: Insights from strategic technology, organizational dynamics, and environmental adaptation. *Socio-Economic Planning Sciences*, *98*, 102124. https://doi.org/10.1016/j.seps.2024.102124

Wang, Y., Zhu, L., & Jin, X. (2024). The effect of a high-performance work system on organizational innovation performance: The mediating effect of employees' intrinsic motivation and the moderating effect of person-organization fit. *Systems*, *12*(7), 230. https://doi.org/10.3390/systems12070230

Wongmahesak, K., Wongsuwan, N., Akkaya, B., & Palazzo, M. (2024). Impact of Knowledge Management Process on Organizational Performance: The Mediating Role of Technological Innovation. *Knowledge and Process Management*, *32*(1), 54-64. https://doi.org/10.1002/kpm.1795

Xu, M., Zhang, Y., Sun, H., Tang, Y., & Li, J. (2024). How Digital Transformation Enhances Corporate Innovation Performance: The Mediating Roles of Big Data Capabilities and Organizational Agility. *Heliyon*. https://doi.org/10.1016/j.heliyon.2024.e34905

Yu, J., & Xiang, K. (2024). Transformational Leadership, Organizational Resilience, and Team Innovation Performance: A Model for Testing Moderation and Mediation Effects. *Behavioral Sciences*, *15*(1), 10. https://doi.org/10.3390/bs15010010

Zarei, M. (2024). The Impact of High-Performance Work Systems on Promoting Organizational Creativity and Innovation Mediated by Knowledge Sharing (Case Study: A Military Organization). *Journal of Marine Science Education*, *11*(4), 13-29.

Zhang, J., Zia, U., Shehzad, M. U., & Sherani. (2025). Tacit knowledge management process, product innovation and organizational performance: exploring the role of affective trust and task efficiency. *Business Process Management Journal*, *31*(1), 267-297. https://doi.org/10.1108/BPMJ-11-2023-0873