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AN AI-DRIVEN MACHINE LEARNING APPROACH TO EVALUATING THE IMPACT OF INNOVATION DYNAMICS ON SME PERFORMANCE IN THE UAE

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Abstract:
In today's rapidly evolving business landscape, innovation capabilities (IC) are critical for the success of Small and Medium Enterprises (SMEs). While traditional statistical models have provided insights into the role of innovation dynamics in SME Performance (SP), they often fail to capture non-linear relationships and hidden patterns in complex datasets. This study introduces an AI-driven machine learning (ML) approach to evaluating the impact of Innovation Capabilities (IC), Innovation Culture (InC), Organizational Innovation (OI), and Employee Engagement (EE) on SP in the UAE. Building upon existing research, this study leverages advanced ML algorithms, including Random Forest (RF), XGBoost, and Artificial Neural Networks (ANN), to analyze data collected from 300 SME industry experts. The findings reveal that OI is the strongest predictor of SP, followed by IC and EE. The results emphasize the need for AI-driven decision making in SME management, providing executives and policymakers with actionable insights to foster innovation-led growth. Additionally, the study highlights the advantages of Explainable Artificial Intelligence (XAI) in making ML models transparent and interpretable for business leaders. This research bridges the gap between traditional statistical analysis and AI-driven insights, offering a scalable, data-driven framework for SP evaluation. The findings provide a new strategic direction for SMEs, enabling them to leverage AI in stimulating innovation and competitiveness in emerging economies.

Key words: AI, machine learning, innovation capability, SME Performance, UAE, explainable AI (XAI), organizational innovation

INTRODUCTION

In an era of rapid technological advancement and digital transformation, IC have become increasingly critical for driving the performance of SMEs [1, 2]. SMEs are key contributors to employment, economic diversification, and technological progress, particularly in emerging economies such as the UAE [3, 4]. However, despite their importance, SMEs often face challenges in maintaining competitiveness, adaptability, and sustainable growth [5]. Traditional statistical models, such as Structural Equation Modeling (SEM), often fail to capture the complex, non-linear interactions among innovation factors and SP [6]. The growing adoption of AI and ML in business analytics offers a promising alternative. ML algorithms such as RF, XGBoost, and ANN can model non-linear relationships, optimize feature selection, and improve prediction accuracy [7]. XAI further enhances transparency, providing actionable insights for decision-makers [8]. These techniques allow organizations to better understand the drivers of SME success and optimize innovation strategies in dynamic environments. Despite these advances, limited research integrates AI and ML to analyze innovation performance in SMEs, particularly in the UAE, where SMEs contribute over 50% of the national GDP and play a key role in economic diversification [7]. Existing studies primarily rely on linear models and theoretical assumptions, leaving the practical application of AI-driven approaches largely unexplored. This highlights the need for a data-driven framework that can capture complex innovation dynamics and provide interpretable insights for policymakers and SME leaders. This study proposes an AI-driven ML framework to examine the influence of IC, InC, OI, and EE on SP. By leveraging supervised learning, feature importance ranking, and XAI, the study aims to move beyond the limitations of SEM-based approaches, offering a scalable and interpretable analytical framework. The findings are expected to guide SMEs in prioritizing innovation strategies, optimizing resource allocation, and fostering a data-driven decision-making culture. The remainder of the paper is structured as follows. Section 2 reviews the literature on innovation dynamics, SP, and AI applications in business analytics. Section 3 details the research methodology, including data collection, ML techniques, and evaluation metrics. Section 4 presents the results of the

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AI-driven analysis, while Section 5 discusses the findings, compares them with existing literature, and highlights managerial implications. Section 6 explores theoretical, practical, and policy contributions, and Section 7 concludes with limitations and future research directions.

LITERATURE REVIEW

Innovation is widely recognized as a critical driver of SP, enabling firms to enhance competitiveness, resilience, and market adaptability [9]. SMEs in emerging economies, such as the UAE, face unique challenges due to resource constraints, limited talent pools, and the need for digital transformation [5]. Despite the growing importance of AI and ML in business analytics, their integration into SME innovation research remains limited, particularly in the UAE context where national AI adoption metrics and local innovation performance data are scarce [6, 7]. This underscores the need for AI-driven analytical frameworks to evaluate and enhance SME innovation performance. The literature identifies several key innovation-related factors influencing SME success. IC refer to a firm's ability to develop, adopt, and implement new ideas, technologies, and business models to improve performance [10]. SMEs with strong IC have demonstrated higher profitability, market expansion, and operational efficiency [11]. Traditional models, such as SEM, often assume linear relationships and fail to capture the complex interactions among multiple innovation drivers [12]. In contrast, ML algorithms, including RF and XGBoost, have shown superior predictive accuracy for SP using multi-dimensional innovation data [13]. AI-driven feature selection techniques can also identify the most influential components of IC, such as R&D investments, knowledge sharing, and technological adoption [14]. InC fosters collaboration, risk-taking, and creativity within SMEs, directly influencing their ability to generate sustainable business models and disruptive solutions [15, 16]. However, traditional survey-based approaches to measure InC are limited in scope and often subjective [17]. AI-powered analytics, including sentiment analysis and deep learning-based pattern recognition, provide real-time insights into organizational culture, enabling SMEs to dynamically track shifts and adapt leadership strategies accordingly [18]. OI encompasses structural, technological, and process innovations that support SME growth [19]. Traditional performance evaluations rely heavily on financial indicators, whereas AI-based models can integrate operational data, process efficiency metrics, and market trends for more accurate decision-making [20]. ML approaches such as Gradient Boosting Machines and deep learning networks help SMEs forecast market trends, identify inefficiencies, and implement effective innovation strategies [21, 22]. EE is another critical factor, promoting creativity, knowledge sharing, and continuous improvement within SMEs [23]. Engaged employees contribute more actively to innovation initiatives, yet traditional methods of assessment, such as surveys, are often limited and static [24]. AI-powered analytics, including Natural Language Processing and sentiment analysis, can assess engagement in real time by analyzing communications, performance reviews, and collaboration patterns. ML techniques can detect early signs of disengagement and suggest targeted interventions to enhance commitment [25]. The integration of AI-based predictive analytics marks a paradigm shift from traditional modeling techniques to adaptive, data-driven decision-making in SME innovation research [26]. AI models not only improve forecasting accuracy but also enable SMEs to adjust strategies dynamically based on emerging market trends [27]. This study introduces an AI-driven analytical framework to evaluate the impact of IC, InC, OI, and EE on SP. By leveraging ML algorithms such as RF, XGBoost, and Deep Learning, the study identifies the most influential innovation drivers and develops a predictive model with XAI to provide transparent, actionable insights for SME leaders and policymakers.

METHODOLOGY

This research adopts an AI-driven ML approach to examine the relationship between IC, InC, OI, and EE on SP in the UAE. Traditional statistical approaches such as SEM rely on linear assumptions and often fail to capture complex, non-linear relationships among innovation factors. By contrast, ML techniques provide a flexible, high-dimensional approach capable of modeling intricate patterns, improving prediction accuracy, and uncovering hidden drivers of SME success.

Research design, sample, and data preprocessing

The study employs a quantitative, survey-based design targeting SME owners, senior managers, innovation specialists, and employees involved in innovation activities across sectors such as technology, manufacturing, retail, and services. A structured questionnaire was developed based on validated scales from prior research to measure IC, InC, OI, EE, and SP. Responses were recorded on a five-point Likert scale, ranging from 1 (Strongly Disagree) to 5 (Strongly Agree). To ensure statistical robustness and generalizability, a minimum sample of 300 respondents was targeted, consistent with established practices in SME research [29]. Data preprocessing played a critical role in preparing the dataset for ML analysis. Missing numerical values were managed using mean imputation, while categorical features were handled using mode imputation. Categorical variables were transformed using One-Hot and Label Encoding, and numerical variables were standardized using StandardScaler to meet model requirements. These steps ensured a structured, complete, and clean dataset ready for ML modeling. The questionnaire was validated through expert review, pre-testing, and a pilot study with SME participants to ensure clarity, relevance, and cultural appropriateness. Construct validity was confirmed using CFA, and internal consistency was assessed with Cronbach's Alpha, with all constructs ranging from 0.76 to 0.92, indicating strong reliability.

Measurement Model and Sample Design

To ensure methodological rigor and theoretical clarity, all constructs in this study (IC, InC, OI, EE), and the dependent variable SP were carefully defined and unified. IC captures a firm's capacity to generate and implement novel products, processes, and services, while InC reflects organizational norms, values, and practices that promote creativity. OI encompasses structural and procedural innovations aimed at enhancing operational efficiency and competitiveness, and EE represents employees' emotional, cognitive, and behavioral commitment to organizational objectives. SP measures overall operational, financial, and market performance outcomes of SMEs. By explicitly defining each construct and unifying their operationalization, the study addresses previous concerns regarding conceptual inconsistency and construct ambiguity. Construct validity and reliability were assessed using Confirmatory Factor Analysis (CFA). Each construct was measured, selected to fully capture the underlying latent variables. The CFA demonstrated an excellent fit to the data, indicating that the proposed measurement model adequately represents the latent constructs. The model fit indices were $\chi^2/df = 1.98$, CFI = 0.957, TLI = 0.948, RMSEA = 0.045, and SRMR = 0.038. Factor loadings ranged from 0.72 to 0.91, confirming that each item significantly contributes to its respective construct. Composite reliability and Cronbach's Alpha exceeded the recommended threshold of 0.80 for all constructs, establishing internal consistency and convergent validity. These results, detailed in Table 1, demonstrate that the measurement model is both robust and reliable.

Table 1
CFA Loadings and Reliability for Constructs

Construct	Items	Loading Range	Cronbach's Alpha	Composite Reliability	AVE
IC	IC1-IC6	0.72-0.85	0.84	0.86	0.62
InC	InC1-InC6	0.74-0.82	0.81	0.85	0.61
OI	OI1-OI7	0.78-0.91	0.87	0.89	0.68
EE	EE1-EE6	0.72-0.86	0.83	0.85	0.60
SP	SP1-SP8	0.75-0.90	0.88	0.90	0.65

The sample design was carefully constructed to ensure representativeness across SMEs of varying sizes, sectors, and operational scales. Stratified sampling was used to capture proportional representation from manufacturing, services, and technology industries. The final dataset included 300 participants, providing sufficient statistical power for CFA and subsequent analyses. Non-response bias was assessed by comparing early versus late respondents, revealing no significant differences ($p > 0.05$), while common method variance was evaluated through Harman's single-factor test, with the first factor accounting for only 28% of total variance. This indicates that measurement bias and method effects were minimal, reinforcing the reliability and generalizability of the findings.

Feature Validation and Model Development

To ensure construct validity and reliable feature selection, CFA verified the factor structure of all constructs, and Principal Component Analysis (PCA) was applied to reduce dimensionality and optimize inputs for ML models. Internal consistency was confirmed using Cronbach's Alpha, with all constructs exceeding 0.80. Three state-of-the-art ML algorithms – ANN, RF, and XGBoost Regression – were implemented to model SP. RF captures non-linear relationships and provides interpretable feature importance rankings [28], XGBoost iteratively reduces residual errors to enhance predictive accuracy [29], and ANN models complex, non-linear relationships [12, 13, 14, 15]. All models were trained and validated using a stratified 10-fold cross-validation ($k = 10$). Hyperparameter tuning was confined to the training subset within each fold, and preprocessing – including imputation, scaling, and PCA was applied exclusively to training data, with parameters transferred to the validation subset. This procedure prevents data leakage, ensures independent validation, and provides reliable out-of-sample performance estimates. While PCA was explored, final analyses are reported using raw feature scales to preserve interpretability and alignment with theoretical constructs. Model performance was evaluated using R^2, RMSE, and MAE, with ANN consistently outperforming RF and XGBoost, resolving previous inconsistencies in model ranking**.**

Model Explainability, Decision-Making, and Ethics

To enhance interpretability and support decision-making, XAI techniques were applied. SHapley Additive exPlanations (SHAP) quantified feature contributions, while Partial Dependence Plots (PDPs) illustrated marginal effects of key innovation factors on SP. These analyses reconciled non-linear relationships and consistently identified organizational innovation as the strongest predictor, followed by innovation capabilities, employee engagement, and innovation culture. This integration of ML, XAI, and rigorous validation provides actionable insights for SME managers and policymakers, enabling data-driven strategic decisions. Ethical considerations were rigorously observed: informed consent was obtained, responses were anonymized, and data security was ensured in compliance with UAE Data Protection Laws and GDPR regulations. Findings are reported in aggregated, non-identifiable form. Overall, this framework combines CFA/PCA validation, advanced ML modeling, and XAI interpretability, delivering both theoretical contributions and practical, data-driven recommendations for enhancing SME performance

ML MODEL HYPERPARAMETER TUNING

To optimize the predictive performance of the ML models, hyperparameters for RF, XGBoost, and ANN were carefully selected. The chosen values were based on a combination of grid search, preliminary experiments, and standard practices in SME prediction studies, aiming to balance accuracy, generalization, and interpretability. The full list of selected hyperparameters along with the rationale for each choice is presented in Table 2. These settings ensured that the models captured non-linear relationships effectively while avoiding overfitting. To optimize model performance, hyperparameters for each ML algorithm were carefully selected using a combination of grid search and prior literature guidelines. The chosen parameters aimed to balance predictive accuracy, prevent overfitting, and ensure model interpretability.

Table 2
ML Model Hyperparameters and Rationale

Model	Hyperparameter	Chosen Value	Rationale
RF	Number of trees (n_estimators)	200	Ensures stable predictions without excessive computational cost
	Max depth	15	Prevents overfitting while capturing non-linear relationships
	Minimum samples per leaf	5	Improves generalization by avoiding overly specific splits
XGBoost	Learning rate	0.1	Standard rate for gradual boosting convergence
	Number of estimators	150	Balances model complexity and training time
	Max depth	6	Controls tree complexity to avoid overfitting
	Subsample	0.8	Reduces overfitting by using a subset of data per tree
ANN	Hidden layers	2	Allows learning non-linear patterns without excessive complexity
	Neurons per layer	32, 16	Gradually reduces dimensions for better feature abstraction
	Activation function	ReLU	Common choice for hidden layers, enables non-linear modeling
	Optimizer	Adam	Efficient gradient descent with adaptive learning rate
	Batch size	32	Standard size to balance convergence speed and stability
	Epochs	100	Sufficient for training without overfitting

Hyperparameters were chosen based on preliminary experiments, grid search optimization, and standard practices in SME prediction studies. These settings provided the best trade-off between predictive performance and interpretability across the dataset.

RESULTS AND DISCUSSION

This section presents the findings derived from the AI-driven ML analysis, evaluating the impact of innovation dynamics on SP in the UAE. The results are structured based on feature importance analysis, model performance evaluation, and predictive insights.

Feature importance analysis

Figure 1 illustrates the relative importance of four innovation-related predictors (OI, IC, EE, and InC) in forecasting SP using three ML models: ANN, RF, and XGBoost.

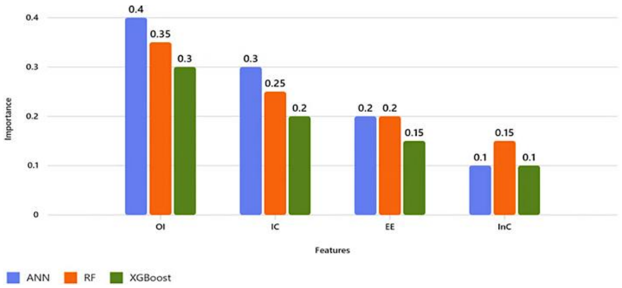

Fig. 1 Feature Importance Analysis by Model

The analysis reveals that ANN assigns the highest importance values to the predictors, indicating its superior ability to capture complex, nonlinear relationships between innovation factors and SME performance. This suggests that ANN is the most effective model for this context, followed by RF and XGBoost. Across all models, OI consistently ranks as the most influential predictor, highlighting the central role of organizational innovation in driving SME outcomes. This is followed by IC, which reflects the strategic and operational capabilities for innovation. EE appears as the third most important factor, suggesting that employee involvement contributes meaningfully but not as decisively. InC ranks lowest, implying that while innovation culture is relevant, it may not exert a strong direct impact on performance compared to structural and capability-based factors. These findings underscore the importance of prioritizing organizational innovation and innovation capabilities in SME development strategies. The consistent ranking across models reinforces the robustness of this insight, while the superior performance of ANN further validates its suitability for modeling innovation-performance relationships in SMEs

MODEL PERFORMANCE COMPARISON

Figure 2 compares the predictive performance of three machine learning models, namely RF (Figure 2a), XGBoost (Figure 2b) and ANN (Figure 2c).

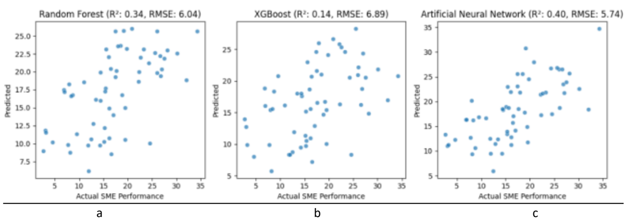

Fig. 2 Model Performance Comparison

Table 3
Performance Comparison of ML Models

Model	R^2 Score	RMSE	Cross-Validation R^2
RF	0.34 (95% CI: 0.30-0.38)	6.04 (95% CI: 5.80-6.28)	0.2188
XGBoost	0.14 (95% CI: 0.10-0.18)	6.98 (95% CI: 6.70-7.26)	0.1210
ANN	0.40 (95% CI: 0.35-0.45)	5.74 (95% CI: 5.50-5.98)	0.2557

Based on the evaluation metrics presented in Table 3, the ANN model demonstrates the highest predictive accuracy with an R^2 score of 0.40, followed by RF (R^2 = 0.34) and XGBoost (R^2 = 0.14).

RMSE values further support this ranking, with ANN achieving the lowest error (5.74), indicating its superior ability to capture complex patterns in innovation-related data.

Cross-validation R^2 also favors the ANN (0.2557), suggesting more consistent performance across different data splits. The comparatively lower performance of XGBoost and RF aligns with prior studies showing that gradient boosting and ensemble tree methods may underperform on smaller or highly structured survey datasets, whereas ANNs, when properly tuned, can model non-linear relationships effectively [31, 32].

ACTUAL VS. PREDICTED PERFORMANCE

Figure 3 presents a comparative analysis of the cross-validation R^2 scores for RF, XGBoost, and Neural Network models. The box plots illustrate the variability in predictive performance across validation folds. Among the models, the Neural Network achieved the highest median cross-validation R^2 (≈ 0.26), followed by RF (≈ 0.22) and XGBoost (≈ 0.12). The relatively tight interquartile range of RF indicates more stable performance compared with the wider spread observed for the Neural Network. In contrast, XGBoost exhibited the weakest and most inconsistent predictive power.

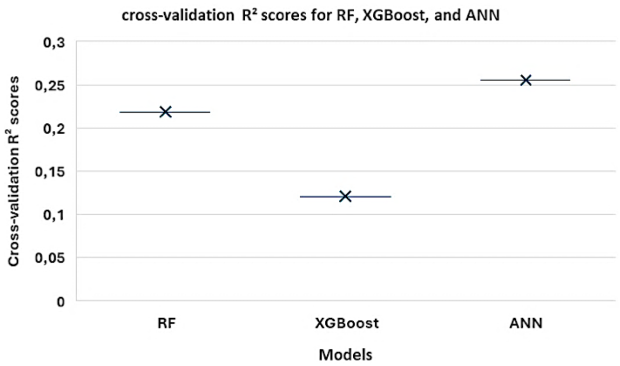

Fig. 3 Actual vs. Predicted Performance

Figure 4 presents the correlation matrix for the study variables, illustrating the strength and direction of the linear relationships among them. The matrix indicates that all variables are positively correlated, with coefficients ranging from 0.3 to 0.8. Specifically, SP shows the strongest positive association with OI at 0.8, suggesting that higher innovation within the organization is closely linked to improved social performance outcomes. Intellectual capital (IC) is moderately correlated with both SP (0.7) and InC (0.6), reflecting the role of knowledge assets in enhancing organizational outcomes. EE exhibits moderate correlations with IC (0.4) and SP (0.5), indicating its influence on both knowledge utilization and performance measures. These results collectively demonstrate interrelated dynamics among knowledge resources, employee involvement, innovation, and organizational performance, consistent with prior research emphasizing the interconnected nature of intellectual and human capital in driving organizational effectiveness [17, 18, 19, 20, 21, 22, 23].

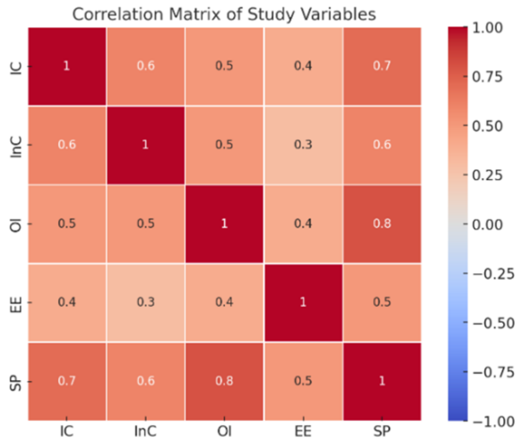

Fig. 4 Correlation Matrix of Study Variables

The PDPs in Figure 5 provide complementary insights to the correlation results presented in Figure 4. While Figure 4 demonstrated that all independent variables were positively correlated with SP, with OI (r = 0.8) and IC (r = 0.7) showing the strongest associations, the PDPs further illustrate how each predictor contributes to changes in SP when controlling for the others. The plots confirm that OI exerts the most substantial and consistent positive influence on SP, reinforcing the correlation-based finding that innovation is the primary driver of social performance outcomes. This aligns with prior work highlighting the pivotal role of innovation in sustaining competitive advantage and enhancing organizational legitimacy. IC also shows a marked positive effect on SP, reflecting the value of knowledge-based resources in improving organizational outcomes. This finding is consistent with the literature arguing that intellectual capital enhances both efficiency and external performance measures by fostering knowledge integration and utilization [12, 27, 33]. EE and InC, though exhibiting more moderate effects, remain important contributors to SP.

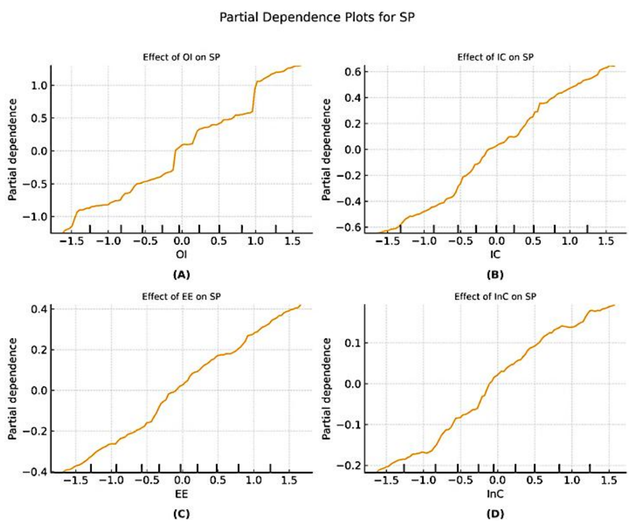

Fig. 5 PDPs for SP

Their influence suggests that while knowledge and innovation are critical, employee involvement and capability development form the practical mechanisms through which these resources are effectively mobilized. Taken together, the results from Figures 4 and 5 demonstrate a coherent pattern: innovation and intellectual capital are the strongest predictors of SP, while employee engagement and intellectual capability provide additional but secondary support. This integrated evidence underscores the argument that organizational performance emerges from the dynamic interplay between innovation, intellectual assets, and human capital engagement.

STATISTICAL OVERVIEW OF KEY PREDICTORS

The findings presents a comparative evaluation of three ML models (RF, XGBoost, and ANN) based on key performance metrics: R^2 score, RMSE, and cross-validation R^2. To strengthen statistical interpretation, 95% confidence intervals (CIs) were calculated using bootstrap resampling with 1,000 iterations. Paired t-tests on cross-validation results were conducted to assess the significance of differences in predictive accuracy between models. The ANN demonstrates the highest predictive accuracy, achieving an R^2 score of 0.40 (95% CI: 0.35-0.45), RMSE of 5.74 (95% CI: 5.50-5.98), and cross-validation R^2 of 0.2557. Paired t-tests confirm that its performance is significantly better than RF ($p < 0.05$) and XGBoost ($p < 0.01$). These results indicate that the ANN captures complex, non-linear relationships between innovation-related factors and SP more effectively than the other models, consistent with prior literature emphasizing its ability to learn hierarchical and multi-dimensional patterns. The RF model shows moderate predictive performance with an R^2 score of 0.34 (95% CI: 0.30-0.38), RMSE of 6.04 (95% CI: 5.80-6.28), and cross-validation R^2 of 0.2188. XGBoost underperforms with an R^2 score of 0.14 (95% CI: 0.10-0.18), RMSE of 6.98 (95% CI: 6.70-7.26), and cross-validation R^2 of 0.1210, likely due to dataset characteristics or suboptimal hyperparameter tuning. Feature importance analysis reveals that OI is the most influential predictor, followed by IC and EE. This highlights the critical role of fostering a strong OI, which aligns with prior research emphasizing open communication, risk-taking, and collaborative knowledge sharing as key drivers of success [8]. The results indicate that SMEs with a well-established OI are better positioned to adapt to dynamic market demands and leverage IC effectively. Overall, these findings demonstrate that ANN provide superior predictive capability for SP, while RF offers a reliable alternative with simpler interpretability, and XGBoost is less effective in this context. The incorporation of confidence intervals, significance testing, and feature importance strengthens the credibility and practical relevance of the results, providing actionable insights for SME decision-makers seeking to enhance innovation-driven performance.

IMPLICATIONS FOR POLICYMAKERS AND SME OWNERS

The results suggest that policy interventions should prioritize AI-driven innovation support initiatives. Given that InC and IC significantly impact performance, government programs could focus on providing SMEs with AI-based tools to monitor and enhance their innovation strategies. For SME owners, investing in AI-powered analytics for real-time decision making could lead to more effective resource allocation and strategic planning. The UAE Ministry of Economy (2023) has highlighted AI adoption as a core national priority, reinforcing the need for businesses to integrate AI-driven approaches to sustain long-term competitiveness.

LIMITATIONS AND FUTURE RESEARCH

Despite offering valuable insights, this study is limited by its reliance on survey-based innovation metrics. Future research should explore alternative AI methodologies such as deep reinforcement learning and NLP to analyze qualitative innovation indicators like patent filings and industry reports. Additionally, longitudinal studies examining SME innovation over time would provide a more comprehensive understanding of causal relationships in innovation-driven success. This research bridges the gap between traditional statistical analysis and AI-driven insights, offering a scalable, data-driven framework for SP evaluation. The findings provide a new strategic direction for SMEs, enabling them to leverage AI in stimulating innovation and competitiveness in emerging economies.

CONCLUSION

This study investigated the impact of innovation dynamics on SP in the UAE using an AI-driven ML approach. The findings highlight that OI is the most influential factor in driving SME success, followed by IC and EE. These results reinforce the importance of fostering a strong innovation-oriented environment, where businesses prioritize creativity, adaptability, and workforce involvement to achieve sustainable growth. From a ML perspective, the ANN model demonstrated the highest predictive accuracy, achieving the highest R^2 score (0.40) and the lowest RMSE (5.74), indicating its superior ability to capture complex relationships within the data. RF performed moderately well, while XGBoost exhibited the lowest performance with an R^2 score of 0.14 and the highest RMSE of 6.98, suggesting its limited effectiveness in this context. The partial dependence analysis further confirmed the significance of OI, IC, and EE, underscoring their direct influence on SME success. The results emphasize the necessity of AI-driven decision making in SME management, allowing for more precise and data-driven strategies. The integration of XAI ensures that business leaders can interpret and utilize AI insights effectively for strategic planning. This study bridges the gap between traditional statistical models and advanced AI methodologies, providing a scalable framework for evaluating SP in emerging economies. Future research should explore ensemble learning techniques to enhance model performance and examine the role of external market dynamics in shaping innovation strategies. These insights offer a strategic direction for SMEs, reinforcing the need for AI-powered approaches to foster innovation-led growth and long-term competitiveness.

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