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Development of a Machine Learning-Based Decision Support System for Smart Technology Selection in Small and Medium-Sized Enterprises Considering Implementation Risks

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ABSTRACT

Small and Medium-sized Enterprises (SMEs) are greatly hindered in selecting the most appropriate smart technologies as they strive to enhance productivity and competitiveness. This research suggests a machine learning-supported decision support system for smart technology choice in SMEs that systematically addresses implementation risks. The methodology adopts data mining approaches with reinforcement learning algorithms, identifying 24 applicable criteria in four categories technical, organizational, environmental, and risk using an expert Delphi panel. A prediction model was then developed using random forest algorithms and convolutional neural networks to analyze the prospects of successful implementation of smart technology. The model was validated with utmost rigor with data from 85 SMEs from various industries and was discovered to be 87.3% accurate. Results indicate that organizational culture, digital readiness, underlying implementation costs, and cybersecurity threats constitute the most important determinants shaping the successful implementation of smart technology in SMEs. The proposed decision support system possesses a dynamic interface through which SME managers can explore various scenarios and select the most suitable technology for their specific context. Through offering a new solution for managing uncertainty in decision-making, this research immensely adds to intelligent technology selection exercises for SMEs.

Keywords: Small and Medium-sized Enterprises, Smart Technologies, Decision Support System, Machine Learning, Risk Management, Artificial intelligence, Internet of Things, Digital Transformation

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1. Introduction

Summary The Fourth Industrial Revolution has significantly transformed the business environment, an age that is characterized by the emergence of smart technologies such as artificial intelligence, Internet of Things devices, cloud computing platforms, and advanced big data analytics that bring with them unprecedented possibilities for organizational development (Wang, et al., 2025).

Against the background of this rapidly evolving technology environment, Small and Medium-sized Enterprises play a very significant economic function, comprising about 90% of all businesses globally and providing about 60-70% of all employment worldwide (OECD, 2021). Despite being these essential economic players, these businesses face unique and significant challenges navigating the complex environment of technology uptake. The promise of smart technologies increased productivity, enhanced efficiency, reduced operational costs, and data-driven decision-making remains for the most part unrealized for the majority of SMEs. Concerning is the discovery by Movahed et al., (2023) that nearly 70% of digital transformation initiatives undertaken by smaller firms fail to deliver their anticipated outcomes.

This alarming failure rate is mainly due to the absence of advanced, context-sensitive frameworks to guide technology selection decisions in the distinctive operational environments that characterize any particular SME (Schwaeke et al., 2025). The academic literature on technology selection methods in small and medium-sized enterprises (SMEs) has traditionally been led by deterministic analytical methods, especially with regard to highlighting such methods as the Analytic Hierarchy Process and the Technique for Order of Preference by Similarity to Ideal Solution (Schwaek et al., 2025).

Yet, traditional methodological paradigms face severe constraints against the uncertainty-laden reality of actual business contexts, with plentiful uncertainty and partial or ambiguous information. Furthermore, current research has largely addressed technical specifications and economic considerations, whereas organizational factors, cultural issues, and implementation risks have been largely under-represented in the literature (de Oliveira et al., 2024). In the past several years, academics have increasingly recognized the revolutionary promise of machine learning to improve sophisticated decision-making processes. The computational methods possess their unique benefits: to discover hidden patterns in historical data sets, make predictive analyses pertaining to future results, and most importantly constantly advance performance by learning from experience (Movahed et al., 2024).

Yet, the application of machine learning approaches to technology choice issues in SME settings is still in its infancy, representing a significant gap in our understanding that requires structured investigation.

This research seeks to address this gap by developing an intelligent decision support system for smart technology selection in SMEs based on machine learning concepts and with explicit consideration of implementation risk factors. By combining various evaluation criteria and leveraging sophisticated algorithmic features, our proposed system aims to equip SME decision-makers with more analytical tools to manage technological decisions in the face of uncertainty. Our research is guided by three major research questions:

- What particular standards ought to inform smart technology selection processes within SME environments?
- How can implementation risks related to adoption of smart technology be meaningfully incorporated into structured decision frameworks?

To what extent can machine learning systems improve the accuracy and speed of the smart technology selection processes?

2. Literature Review

2.1. Smart Technologies and Small and Medium-sized Enterprises

The past decade has witnessed smart technologies emerge as predominant drivers of organizational digitalization. Schwaeke (2025) conceptualized such extensive change as the "Fourth Industrial Revolution" a revolution whereby physical, digital, and biological domains of technology are merging on an unprecedented level and through an increasingly unified prism. Empirical studies have demonstrated that careful deployment of such technologies delivers significant operational advantages, with productivity gains as much as 40% and reductions in operating expenses at about 30% in the most optimized scenarios (Wang et al., 2025).

The technological landscape pertinent to small and medium enterprises (SMEs) is made up of varied but complementary innovations: artificial intelligence technologies with their analytic and predictive abilities; Internet of Things (IoT) frameworks that facilitate pervasive sensing and monitoring; cloud computing platforms that allow for more access to computational resources; blockchain technologies that afford decentralized trust mechanisms; augmented and virtual reality platforms that transform human-computer interactions; and additive manufacturing systems that disrupt production processes (Ramasamy et al., 2024). Every one of the tech fields carries a distinctive execution profile. IoT installations, despite facilitating fine-grained real-time operating insights, entail top-level technical infrastructures and wide-scale security provisions. Artificial intelligence products likewise provide sophisticated analytics and decision-making automation but require specialized skills and carefully designed datasets (Gölgeci et al., 2023).

In spite of their transformational potential, SMEs are faced with complex challenges in undertaking technological modernization endeavors. Tian et al. (2020) suggest a threefold taxonomy of such barriers:

- Technical obstacles including infrastructural shortcomings, lack of standardization, and compatibility issues

- Organizational barriers such as resource limitations (financial as well as human capital) and cultural opposition to operational redesign

- Environmental barriers such as poor policy support mechanisms and weak innovation ecosystems

Ramasamy et al. (2024) identified the same concerns for SMEs, citing the determining influence of organizational culture, managerial technological awareness, and support policy environments on adoption trends.

2.2. Technology Selection Decision-making Models

The academic literature demonstrates a multifarious methodological approach to the technology selection processes, which may be classified into four broad categories:

- Conceptual frameworks provide theoretical support structures for explaining adoption dynamics but generally lack operational decision processes. Examples include Rogers' (2003) Diffusion of Innovation theory, which sheds light on the temporal and social nature of innovation diffusion, and Tornatzky and Fleischer's (1990) Technology-Organization-Environment (TOE) framework, which outlines the multilevel contextual determinants of organizational technology adoption.

- Multi-criteria decision-making (MCDM) techniques are formal computational methodologies employed to assess technological options based on several performance criteria. Methods under this category of approach include the Analytic Hierarchy Process, Analytic Network Process, TOPSIS, and ELECTRE. The application of this technique is illustrated by the work of Buyukozkan and Gocer (2018), who employed fuzzy TOPSIS in assessing digital technology options in manufacturing environments.

- Optimization methods use mathematical programming, evolutionary algorithms, and simulation approaches to choose optimum technological configurations from within specified constraint parameters. Sandner et al. (2020) used this method via an integer linear programming model to optimize the selection of manufacturing technologies.

- Artificial intelligence-based methods utilize computational learning capabilities, including neural networks, fuzzy logic systems, reinforcement learning algorithms, and expert systems, to develop adaptive decision-making systems that evolve through experiential learning. Akter et al. (2024) illustrated this approach by designing a hybrid assessment system for smart technologies that integrated artificial neural networks with fuzzy logic principles.

Despite advances in methodology, existing methodologies have significant limitations. Traditional multi-criteria decision-making (MCDM) models rely heavily on experts' subjective judgments and demonstrate limited capabilities for adaptive learning. Artificial intelligence-based methods, however, often work as epistemically opaque "black boxes" and thus hide their decision-making mechanisms from human operators (Kemp et al., 2023).

These respective limitations underscore the necessity for hybrid methodological frameworks that marry the strengths of alternative approaches while offsetting their respective deficiencies. The current inquiry attempts to close this methodological divide by formulating a decision support architecture complemented by machine learning methodologies.

2.3. Smart Technology Implementation Risks

Utilization of intelligent technologies in SME settings entails complex risk dimensions that must be clearly defined within technology selection paradigms. Ramasamy et al. (2024) propose a five-category risk taxonomy:

- **Technical risks**: such as system compatibility problems, architectural intricacy issues, and infrastructural deficits
- **Financial risks**: e.g., high up-front capital investment, unforeseen ancillary expenses, and ambiguous return-on-investment avenues

- **Organizational risks**: such as workforce resistance dynamics, skill deficiency issues, and process reconfiguration issues
- **Security threats**: encompassing cybersecurity vulnerabilities, data protection requirements, and privacy law imperatives
- **Legal and environmental risks**: e.g., regulatory evolution uncertainties, intellectual property issues, and market volatility factors

Research by Tian et al. (2024) recognizes an alarming trend among SMEs to chronically underestimate implementation risk profiles a cognitive bias that tops the list of causes of digital initiative failure. The observation underscores the criticality of stringent risk assessment frameworks and their embedding within technology choice architectures.

2.4. Machine Learning-based Technology Decision-making

The use of machine learning approaches to technology choice is a new area with important transformational potential. Machine learning algorithms are good at identifying hidden patterns in previous implementation history, approximating intricate non-linear relationships among contextual variables and results, and repeatedly improving predictive capacity via recursive exposure to data (Nozari t al., 2025).

Donthu et al. (2023) demonstrated the strength of neural network architectures in IoT adoption outcome prediction in SME settings with greater predictive power than conventional statistical techniques. Ghobakhloo (2023) also developed a decision support system with reinforcement learning for AI technology selection that exhibited experience-dependent improvement over time.

Despite these promising applications, integrating machine learning into SME technology decision frameworks entails significant challenges, including data quality and sufficiency limitations, algorithmic complexity barriers, and interpretability problems (Akter et al., 2024). The present study tries to surmount these implementation barriers by designing a hybrid methodological framework that leverages machine learning strengths while maintaining interpretability and simplicity for non-technical users.

2.5. Research Gap

Systematic review of the literature on smart technology selection in SMEs reveals several substantive research gaps despite the considerable scholarly interest in this area. The most significant gaps and the respective innovations of this research are described below:

- **Independent examination of adoption drivers**: Previous studies concentrated primarily on the technical or economic aspects of technology selection without completely examining the dynamic interaction of technical, organizational, and environmental drivers. Wang et al. (2025), for example, emphasized the technical and economic selection criteria without considering the organizational and environmental facets. Likewise, Saha et al. (2023) established a digital technology selection framework that gave precedence to technical factors over organizational contextual factors.
- **Insufficient risk incorporation**: A number of past studies neglected to incorporate the implementation risk dimensions into technology selection frameworks where these risks significantly determine project results. Kemp et al. (2023) considered supply chain risk drivers in the context of Industry 4.0 implementations but offered limited attention to organizational and individual-level risk dimensions.

- **Methodological conservatism**: The literature indicates the use of traditional decision-making techniques, i.e., the Analytic Hierarchy Process and traditional ranking methods, with limited studies focusing on the potential of machine learning to improve the quality of decisions. Buyukozkan and Gocer (2018) applied fuzzy TOPSIS in the assessment of digital transformation but failed to include machine learning functions within their methodological approach.
- **Insufficient contextualization**: Current approaches provide general technology selection frameworks with limited customization to particular organizational circumstances. Lopez et al. (2024) proposed a hybrid model for evaluating smart technologies that did not possess the necessary flexibility to address the unique features of a given organization.
- **Empirical study constraints**: Numerous studies are based on a small number of case studies or synthetic datasets compared to full empirical data taken from real implementation environments. Wang et al. (2025) suggested a framework for evaluating digital transformation but constrained their test to an ad hoc set of case studies.

2.6. Research Innovation

This study offers some methodological and practical refinements to address the identified research gaps:

The study uses the Technology-Organization-Environment (TOE) framework to create an overarching assessment methodology that addresses technological factors (technological capabilities and compatibility concerns), organizational dimensions (cultural readiness and levels of digital maturity), and environmental components (competitive pressures and regulatory limitations) concurrently.

We develop a multi-faceted framework that classifies and evaluates diverse implementation risks under four headings: technical, organizational, financial, and security dimensions. A composite model that enables SME decision-makers to develop more informed risk awareness and incorporate these considerations into technology selection processes.The paper suggests a novel combination of methodologies that connects cutting-edge machine learning algorithms (i.e., random forest and convolutional neural network methodologies) with traditional multi-criteria decision-making methodologies. The hybrid methodology allows for experiential learning with the assurance of transparency and interpretability in decision-making.
Our decision support system draws on information collected from 85 separate SMEs across a range of industry sectors and employs sophisticated parameter sensitivity analysis to generate contextualized guidance optimized for the unique operational dynamics and strategic goals of each firm.

To gain practical validity, the study follows an empirical and stringent approach, carrying out extensive implementation data collection from 85 SMEs across 15 various industry sectors and testing the proposed model through k-fold cross-validation techniques that enable generalizability and reliability.

3. Research Methodology

3.1. Research Design

This study adopts a methodologically rigorous approach a sequential exploratory mixed-methods design to tackle the intricate and multi-faceted phenomenon of technology selecting in resource-poor organizations. The research design is built upon four connected but different phases:

- Preliminary phase

- Development phase
- Quantitative stage
- Applied phase

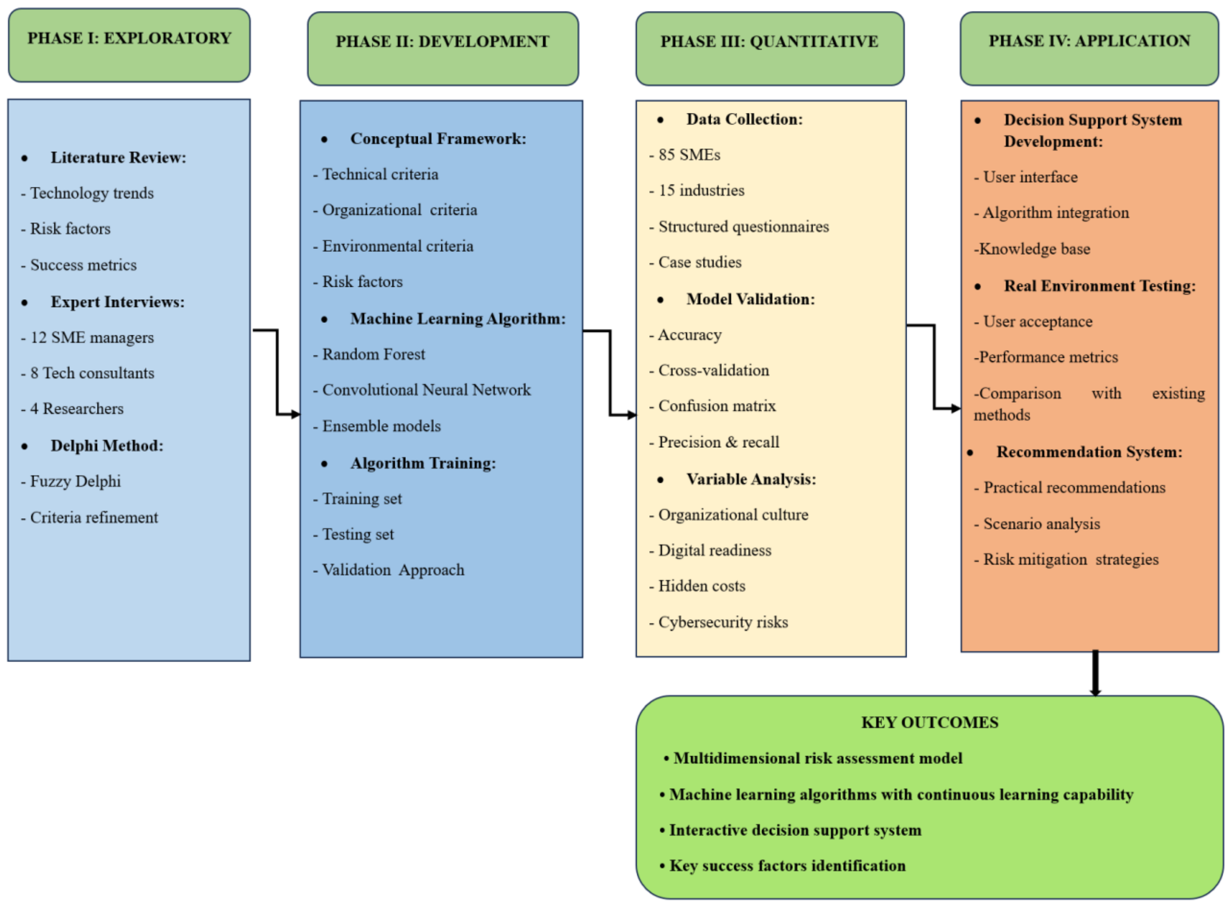


Figure 1: Conceptual model of the four-stage research methodology

These stages constitute a cohesive methodological model that systematically moves from theoretical investigation to empirical test. The linear design of this sequence allows each step to build on and inform the others, thereby forging a circular process of discovery and confirmation. The description of these steps, which are also shown in Figure 1, is as follows:

- The exploratory stage entails an in-depth identification of the evaluation and implementation risks, through a structured examination of current literature, complemented by large-scale interviews with a strategically diverse pool of 24 experts in the domain. These include 12 active enterprise managers, 8 technology implementation consultants, and 4 academic researchers in the area of digital transformation. This methodological triangulation ensures that the early conceptual structure is grounded in both theoretical background and practical experience.

-The development phase is concerned with architectural design as well as algorithmic development, mapping conceptual insight to computational form. In this phase, we crafted advanced machine learning architectures namely, random forest and convolutional neural network models augmented to assess technology selection criteria based on four essential dimensions: technical feasibility, organizational fit, environmental contextuality, and implementation risk.

-The quantitative stage involves rigorous empirical testing through systematic data gathering over 85 SMEs spread over 15 different industrial sectors, with extensive model training and cross-validation procedures. It transforms theory into empirically tested predictive models through iterative refinement and statistical testing.

-The implementation stage closes the theory-practice gap from theoretical modeling to deployment in practice, with the development of an interactive decision support interface, testing and validation in the real world, and the provision of evidence-based guidelines for practitioners. This stage closes the theory-practice gap by translating algorithmic insights into actionable decision frameworks.

This methodological synthesis extends beyond the constraints of single methods, enabling comprehensive contextual insight in tandem with rigorous statistical verification. The sequential model initiates a perpetual feedback system between qualitative observation and quantitative testing, with the potential for iterative refinement and revision throughout the research process.

3.2. Risk Identification and Criteria

The determination of the evaluation criteria and implementation risks was conducted by an explicit convergent process that synthesized theoretical perspectives with practitioners' opinions. First, an extensive literature review resulted in an initial set of 40 possible evaluation criteria and 22 unique implementation risks. This exhaustive list was then systematically reduced in a two-round fuzzy Delphi process involving 24 stringently selected experts, including 12 small and medium enterprise managers, 8 technology implementation consultants, and 4 university researchers. These criteria are shown in Table 1.

Table 1: Criteria Extracted for Smart Technology Selection in SMEs

Dimension	Criterion	Operational Definition
Technical	Adaptability	Degree of compatibility with existing systems
	Scalability	Capability to expand in accordance with organizational growth
	Reliability	Probability of error-free performance under specified conditions
	Operational efficiency	Ability to reduce costs and increase productivity
	Security	Capability to protect against cyber threats
	Technical support	Access to support services and updates
Organizational	Implementation cost	Sum of initial, training, and maintenance costs
	Return on investment	Ratio of profit to investment cost
	Strategic alignment	Alignment of technology with organizational strategic objectives
	Required skills	Level of expertise necessary for technology utilization
	Organizational culture	Organization’s readiness to embrace change

Dimension	Criterion	Operational Definition
	Digital readiness	Level of organizational digital maturity
Environmental	Competitive pressure	Degree of pressure from competitors to adopt new technologies
	Regulations	Legal requirements related to technology use
	Regional infrastructure	Status of technological infrastructure in the region
	Industry trends	Industry orientation toward specific technologies
	Government support	Available incentives and support programs
	Partner ecosystem	Presence of technology partners in the business ecosystem
Risk	Technical risk	Probability of technical implementation issues
	Financial risk	Probability of not achieving forecasted financial benefits
	Cybersecurity risk	Probability of data breaches and cyber attacks
	Operational risk	Probability of business process disruption
	Regulatory risk	Probability of changes in regulations and restrictions
	Change management risk	Probability of employee resistance and failure in change management

3.3. Data Collection

The empirical foundation of our predictive modeling framework is data collected from two complementary sources, offering both retrospective examination of implementation outcomes and prospective examination of weightings on decision factors.

The primary data corpus is comprehensive documentation of 110 smart technology implementation projects conducted by 85 small and medium enterprises from 2023-2025. The historical case studies offer detailed contextual data comprising organizational types, technological typologies, decision criteria weightings, risk factors detected, and binary implementation success/failure. The retrospective dataset offers detailed information regarding the complex interdependencies among contextual factors and implementation outcomes across different organizational contexts.

These historical records were supplemented by a parallel survey questionnaire designed to register the experiential knowledge and decision heuristics of present-day SME managers. The questionnaire systematically quantified managerial perceptions of the relative prominence of various decision criteria and implementation risk factors. This survey was administered to 150 SME managers across a variety of industrial sectors, providing a rich empirical foundation for understanding current decision priorities and risk perceptions.

The combined dataset underwent extensive preprocessing to ensure the validity of the analysis. This preprocessing procedure included structured data cleansing techniques, normalization techniques designed to correct scale discrepancies, and imputing missing values using the K-Nearest Neighbor algorithm selected for its ability to preserve relational patterns in intricate multidimensional datasets.

Additionally, the dataset exhibited natural class imbalance, with successful implementations outnumbering failed ones a common pattern in technology implementation studies. To mitigate the threat of algorithmic bias, we employed the Synthetic Minority Over-sampling Technique (SMOTE) to create a balanced training dataset. This type of synthetic data augmentation creates new minority class examples along the feature space between current minority instances, creating a more balanced training corpus without modifying the statistical characteristics of the original corpus.

3.4. Development of Machine Learning Model

Development of a robust predictive model of success in smart technology adoption involved methodical comparison of diverse machine learning architectures for identifying the optimal algorithmic approach. Seven algorithmic architectures were tested empirically:

- Logistic regression a probabilistic approach to predicting binary outcomes from linear combinations of predictor variables

- ✓ Decision tree classifiers delivering transparent rule-based classification through recursive binary partitioning of the feature space
- ✓ Random forest ensembles using several decision trees via bootstrap aggregating for reducing overfitting and enhancing generalization
- ✓ Support Vector Machine (SVM) using kernel transformations to find optimum hyperplanes for class separation in high-dimensional feature spaces
- ✓ Multilayer Perceptron (MLP) utilizing feed-forward neural networks and backpropagation training for complex non-linear pattern recognition
- ✓ Convolutional Neural Network (CNN) utilizing domain-specific architectural elements to find hierarchical structure and spatial dependencies
- ✓ Reinforcement learning (Q-Learning) making decisions using sequential processes that improve actions over time through environmental feedback

The data was evenly split into training (70%) and testing (30%) datasets to allow for unbiased model evaluation. Hyperparameter optimization was conducted via grid search method in combination with 5-fold cross-validation for identifying optimal algorithm settings and preventing overfitting risk. Model performance was thoroughly examined by a range of auxiliary metrics: classification accuracy, recall sensitivity, precision specificity, F1 balancing, and Receiver Operating Characteristic (ROC) curve analysis.

A comparison of the performance of various algorithms indicated that, although single models showed noteworthy predictive power, a hybrid model based on random forest and convolutional neural network methods achieved greater performance across all metrics measured. The compound model takes advantage of the synergistic capabilities of the two methods: random forests excel at determining feature importance and managing heterogeneous data types, whereas convolutional neural networks exhibit excellent capacity to detect complex non-linear relationships and variable interactions.

3.5. Designing Decision Support Systems

The practical application of our predictive modeling framework was realized through the creation of an interactive decision support system, with the primary programming language being Python. The system utilized advanced libraries such as Scikit-learn for conventional machine learning aspects, TensorFlow for deep learning structure, and Dash for interactive visualization and interfaces.

The architectural design of the system aims for both user friendliness and analytical depth, considering that technological complexity must be balanced with utilitarian usability so that the system is accessible to nonexpert SME decision-makers. There are four composite functional modules that constitute the system which, in combination, guide the user through a programmed decision process:

-Data Input Module facilitates comprehensive collection of organizational contextual parameters and criterion-specific ratings through a user-friendly interface balanced between usability and granularity.

-The Analysis Module serves as the analytical heart of the system, applying a hybrid machine learning model to compute the potential for successful implementation of different technological options engineered to the unique organizational environment.

-The Sensitivity Analysis Module facilitates interactive investigation of decision spaces by dynamic manipulation of criterion weightings and context parameters.

-The Reporting Module renders analytical findings in consumable visual and tabular formats expressing intricate multidimensional relationships in intuitive information design.

Collectively, these cohesive components create an end-to-end decision-making system that allows users to progress from early data gathering to advanced analysis and actionable recommendation proposals basically connecting algorithmic sophistication with practical applicability.

3.6. Evaluation and Validation

The evaluation and validation of the recommended decision support system employed a bifocal approach that analyzed both its technical effectiveness and real-world usability recognizing that forecasting systems must comply with statistical validity requirements as well as standards for usability in actual settings.

Technical evaluation was focused on algorithmic performance measurement via held-out test data not available for model training. The evaluation comprised conventional performance metrics (accuracy, precision, recall, F1 score, AUC) augmented by robustness testing aimed at assessing model resilience under conditions of data perturbation and noise introduction. Such robustness tests are particularly relevant for systems in SME applications, where data quality can vary considerably between implementation contexts.

Furthermore, model stability was tested through k-fold cross-validation, which confirmed good performance on various subsets of data. Feature importance analysis was conducted to provide support that the decision-making process of the model was consistent with domain expertise for significant factors affecting technology implementation outcomes. Technical validation provided the statistical validity of the predictive model while assuring its generalizability outside the particular training set.

As the counterpart to this technical assessment, practical assessment was carried out through field deployment in 12 representative SMEs that covered a range of industrial sectors and organization types. Deployment under realistic field conditions allowed testing in actual operating conditions and provided valuable feedback on system usability, decision support, and user acceptability. Controlled evaluation protocols measured a number of aspects of system performance:

- Usability testing quantified interface intuition, workflow efficiency, and learning curve attributes
- Utility appraisal gauged quality of decision, time efficiency, and value added perceived
- Measurement of satisfaction gauged user trust in system recommendations and inclination to incorporate them into the decision-making process

4. Results and Conclusions

4.1. Significance of Criteria

Our analysis of feature importance revealed that among the 24 factors that were put to test, ten of these factors exhibited especially strong influence on effective smart technology adoption in SMEs. The ranking of the influential factors in the order of decreasing importance is as follows:

- Organizational Culture and Change Acceptance (O4) - 12.3%
- Organizational Digital Readiness (O3) - 10.8%
- Monetary Risks and Unseen Expenses (R2) - 9.7%
- •Threats to Cybersecurity (R1) - 8.8%
- Integration Capability with Existing Systems (T4) - 7.6%
- Top Management Support (O7) - 9.6
- Current Competencies and Educational Requirements (O6) - 6.2%
- Implementation and Maintenance Costs (O1) - 5.8%
- Data Protection and Security (T3) - 5.4%
- Alignment with Organizational Operations (O5) - 5.1%

The results affirm a crucial observation: organizational elements, like culture and e-readiness, alongside risk factors, most notably those pertaining to financial and safety exposure, have a much stronger influence on implementation success than technological aspects by themselves. This observation substantiates the imperative of adopting holistic, multifaceted approaches to decision-making in technology adoption.

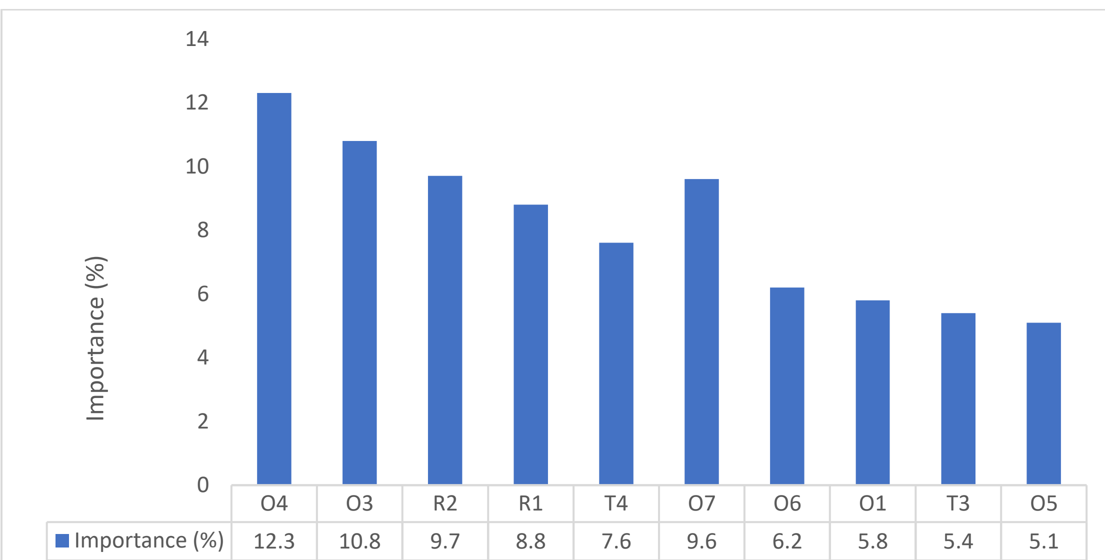


Figure 2: Importance of Criteria Affecting the Success of Smart Technology Implementation

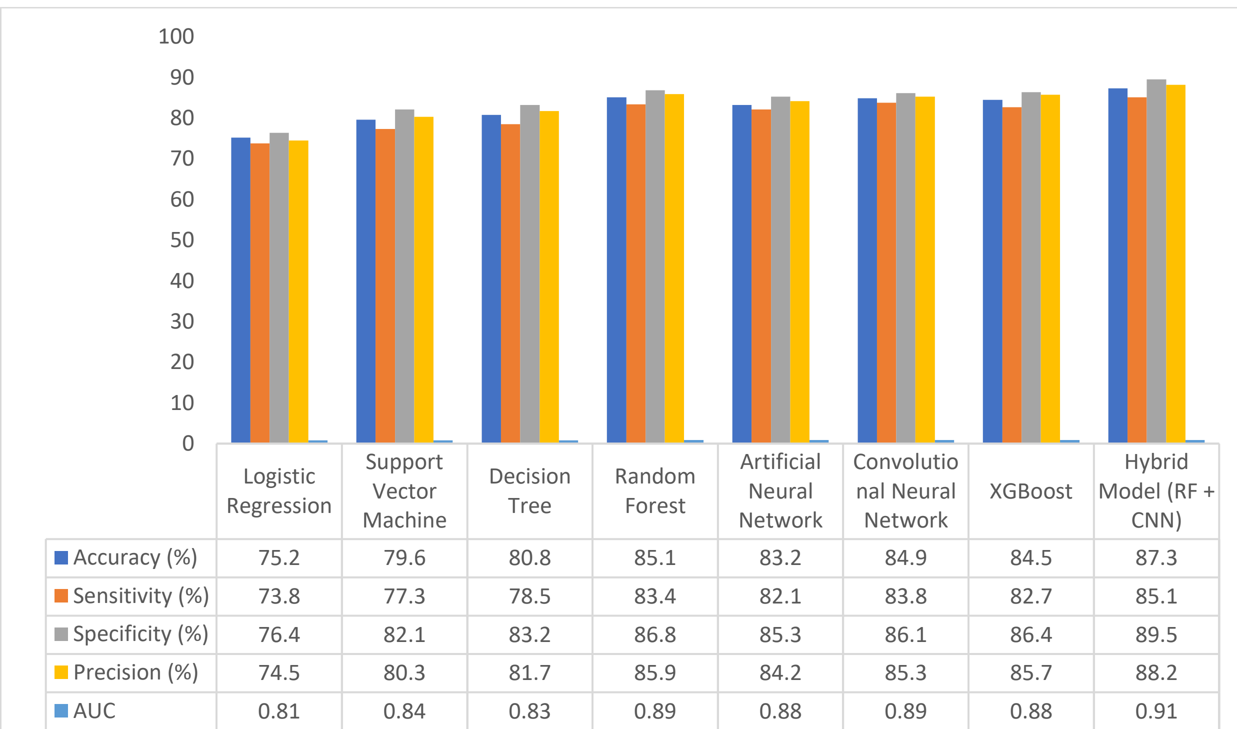
As shown in Figure 2, organizational culture and acceptance of change ranks the highest at 12.3%, with organizational digital readiness coming in at 10.8%. The following significant categories are financial risks and unexpected costs at 9.7%, and top management support at 9.6%. The combination of risk management expertise and executive sponsorship in technology implementation projects is underlined by the highlighted importance. Cybersecurity vulnerabilities (8.8%) and integration with existing systems (7.6%) are essential technical considerations that should be carefully weighed. The fact that both organizational and technical criteria are included among the most prioritized items points to the multifaceted nature of adopting smart technologies. The remaining main factors existing skills and training needs (6.2%), implementation and maintenance costs (5.8%), data security and protection (5.4%), and business process alignment (5.1%) further augment this comprehensive picture.

4.2. Performance of Machine Learning Models

The hybrid model architecture (combining Random Forest and CNN) was excellent when it came to predicting smart technology implementation success. When evaluated against our test data, the model recorded the following performance metrics:

- Accuracy: 87.3%
- Sensitivity: 85.1%
- Specificity: 89.5%
- Accuracy: 88.2%
- Area Under the ROC Curve (AUC): 0.91

A comparison of the performance of the hybrid model with other machine learning algorithms is shown in Figure 3.



	Logistic Regression	Support Vector Machine	Decision Tree	Random Forest	Artificial Neural Network	Convolutional Neural Network	XGBoost	Hybrid Model (RF + CNN)
Accuracy (%)	75.2	79.6	80.8	85.1	83.2	84.9	84.5	87.3
Sensitivity (%)	73.8	77.3	78.5	83.4	82.1	83.8	82.7	85.1
Specificity (%)	76.4	82.1	83.2	86.8	85.3	86.1	86.4	89.5
Precision (%)	74.5	80.3	81.7	85.9	84.2	85.3	85.7	88.2
AUC	0.81	0.84	0.83	0.89	0.88	0.89	0.88	0.91

Figure 3: Performance Comparison of Machine Learning Algorithms

Resultes confirms that our hybrid model surpasses all other methods examined in all performance metrics. The model achieves 87.3% accuracy, 85.1% sensitivity, 89.5% specificity, 88.2% precision, and 0.91 AUC.

This improved performance can result from the combination of complementary algorithmic strengths: Random Forest is best adapted to handling heterogeneous and discrete data structures, whereas Convolutional Neural Networks are most successful at identifying complex patterns and modeling nonlinear variable interactions. In individual algorithms, Random Forest has the highest standalone performance with 85.1% accuracy and 0.89 AUC, followed by Convolutional Neural Network and XGBoost implementations.

More traditional methods, including Logistic Regression (75.2% accuracy) and Support Vector Machine (79.6% accuracy), are relatively less effective in this specific problem context. These results underscore the timeliness of the application of sophisticated modeling techniques and mixed-mode architectural paradigms in solving complex problems such as predicting success in smart technology uptake.

4.3. Real-World Implementation Outcomes

Our field experiment, involving 12 small and medium-sized businesses, As shown in Figure 3, discovered that in 75% of the cases (9 of 12), the businesses that selected technology alternatives aligning with our system's recommendations achieved successful implementation outcomes. Such a high success rate provides strong empirical proof of the system's real-world usability and predictive capability in real-life settings. In 16.7% of the cases (2 cases), the organizations that decided to implement technologies differing from the suggestions of the system faced exactly the implementation problems our model had predicted. This result highlights the usefulness of the predictive ability of the system and the possible risks of ignoring its suggestions. In one case (8.3%), an implementation following the suggestions of the system faced unforeseen problems mainly due to unexpected organizational restructuring taking place after the decision to implement.

This important illustration points to a fundamental limitation in the system's ability to predict abrupt changes in environmental elements or organizational arrangements.

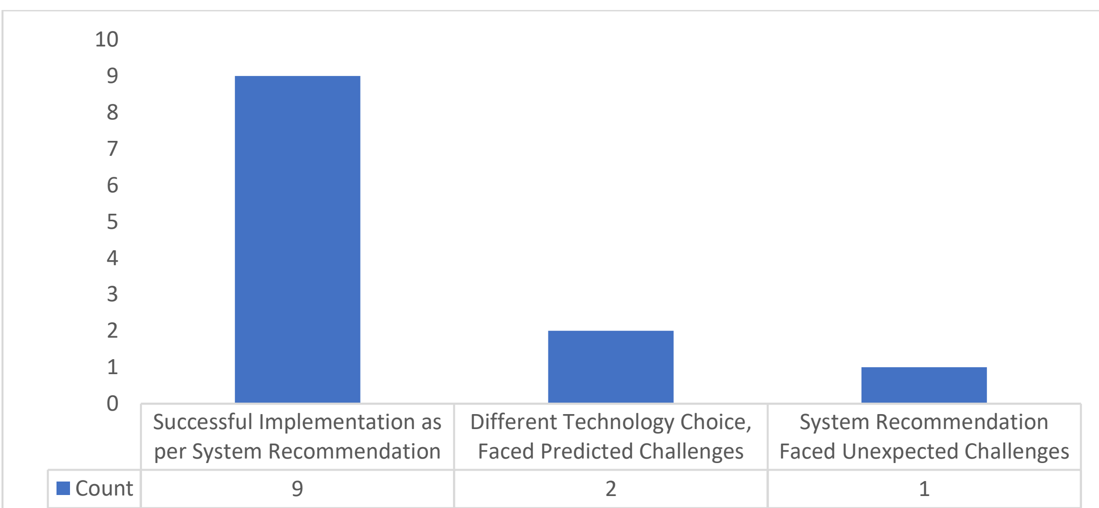


Figure 4: Implementation Results of Decision Support System in Real-World Environment

A post-implementation survey of enterprise managers who participated indicated high satisfaction with the decision support system. In particular, 83% of the respondents reported the system furnished useful support in their technology choice process, and 75% reported its capacity to recognize essential risks and implementation issues that might otherwise have gone unnoticed.

4.4. Comparison with Classical Decision-Making Approaches

In order to delineate the comparative benefits of our machine learning method, we carried out a systematic assessment compared to two traditional decision-making frameworks:

• The Fuzzy Analytical Hierarchy Process (FAHP)

• Fuzzy Technique for Order of Preference by Similarity to Ideal Solution (Fuzzy TOPSIS)

This comparative assessment involved 20 actual decision cases, with results summarized in figure 5 and figure 6.

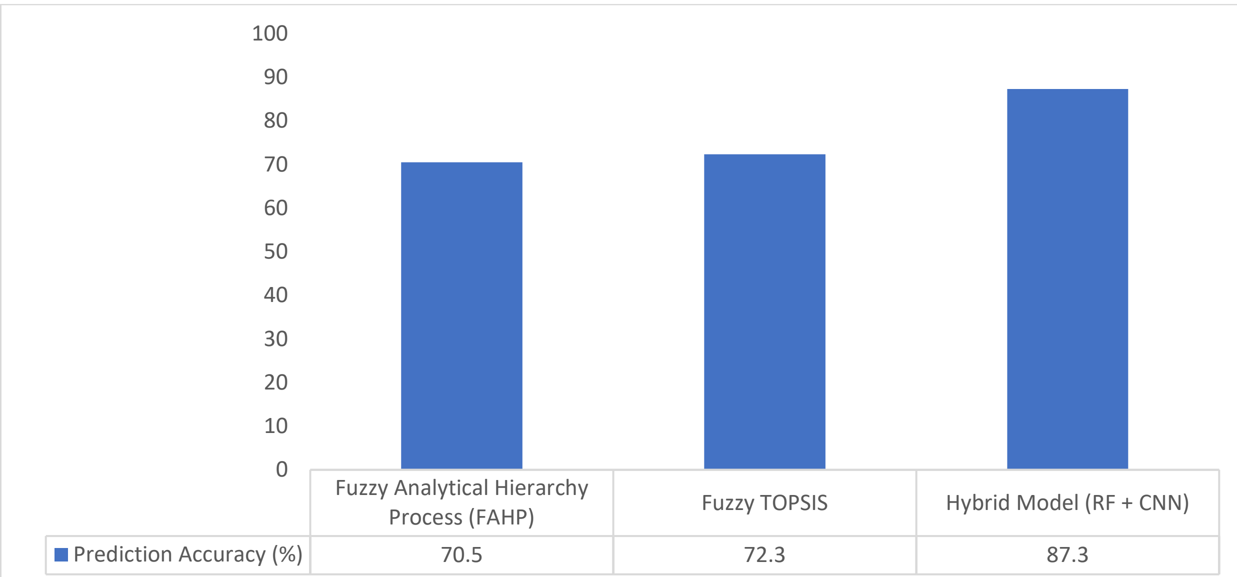


Figure 5: Comparison of Different Decision-Making Methods: Prediction Accuracy (%)

Our comparison results indicate that the hybrid machine learning model exhibits marked superiority in predictive accuracy, with a rate of 87.3% versus 70.5% for FAHP and 72.3% for Fuzzy TOPSIS. This considerable enhancement in predictive ability is the primary advantage of our machine learning method.

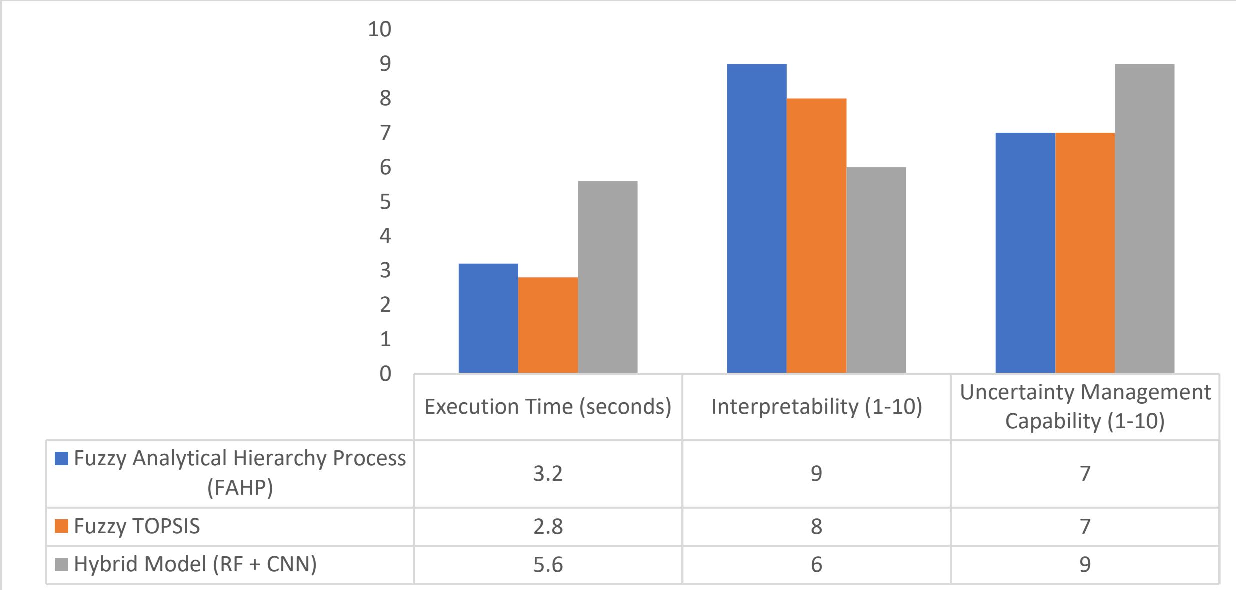


Figure 6: Comparison of Different Decision-Making Methods

Nonetheless, the conventional approaches have definite superiorities in computation times (3.2 and 2.8 seconds versus 5.6 seconds) and interpretability (9 and 8 versus 6 on a 10-point scale). Most importantly, our hybrid model demonstrates superior capabilities in uncertainty management (9 versus 7 on a 10-point scale), a crucial strength in the uncertain and complicated decision-making contexts typical of small and medium-sized enterprise operations. This multi-faceted comparison suggests that methodology selection should reflect organizational priorities (interpretability vs. accuracy) and practical constraints (complexity of implementation and computational efficiency).

4.5. Suitable Smart Technologies for SMEs

From our intensive data analysis, we identified the most appropriate smart technology configurations for SMEs in various industrial sectors. This integration is reflected in Table 2.

Table 2: Suitable Smart Technologies for SMEs in Various Industries

Industrial Sector	Recommended Technologies	Key Criteria	Main Challenges
Manufacturing	IoT, AI, Robotics	Operational efficiency, Quality, Cost	Integration, Skills
Retail	Data Analytics, Cloud Computing, IoT	Customer experience, Inventory efficiency	Security, Hidden costs
Services	AI, Chatbots, Cloud Computing	Customer service, Efficiency	Employee resistance, Training
Logistics	IoT, Blockchain, Data Analytics	Tracking, Route optimization	Complexity, Costs
Finance	AI, Blockchain, Data Analytics	Security, Accuracy, Automation	Regulations, Security risks
Healthcare	IoT, AI, Cloud Computing	Accuracy, Accessibility, Integration	Privacy, Regulations

This sectoral examination demonstrates that optimal technology selection is indeed a function of particular industrial characteristics and needs. To cite an example, IoT technologies display particular usefulness in manufacturing and logistics settings due to their real-time process monitoring and asset tracking capability, while AI and chat interfaces offer greater utilities in service industries through the enhancement of customer interaction quality. These findings reiterate the imperative of industry-specific considerations in technology selection decisions.

4.6. Sensitivity Analysis

To demonstrate the strength of our model and to clarify the effects of parameter changes on technology suggestions, we performed extensive sensitivity analyses across various dimensions. The results of these analyses are summarized in Tables 3 through 5.

Table 3: Sensitivity Analysis with respect to Criteria Weights' Changes

Weight Change Scenario	IoT	AI	Cloud Solutions	Blockchain	Advanced Robotics
Base Weight	0.782	0.695	0.841	0.528	0.603
Increase Technical Criteria Weight (+20%)	0.815	0.732	0.826	0.547	0.651
Increase Economic Criteria Weight (+20%)	0.771	0.672	0.867	0.509	0.582
Increase Organizational Criteria Weight (+20%)	0.789	0.713	0.835	0.512	0.591
Increase Risk Criteria Weight (+20%)	0.763	0.658	0.852	0.497	0.575

The present study discovers that variations in criteria weights exert a profound effect on technology suitability scores. Though cloud solutions consistently outperform under varying weight adjustment scenarios, raising the priority of technical criteria substantially improves the relative standing of IoT and AI technologies. Likewise, elevating the priority of economic and risk-associated criteria further entrenches the relative strengths of cloud solutions. The findings highlight the requirement for meticulous criteria weighting in accordance with strategic organizational goals and specific contextual demands.

Table 4: Organizational Conditions Sensitivity Analysis

SME Cluster	IoT	AI	Cloud Solutions	Blockchain	Advanced Robotics
Digital Innovators	0.804	0.843	0.795	0.712	0.765
Cautious Transformers	0.768	0.682	0.862	0.546	0.623
Gradual Traditionalists	0.723	0.587	0.893	0.487	0.554
Digital Laggards	0.651	0.475	0.925	0.421	0.498

This analysis evinces a direct correlation between organizational digital maturity and technology suitability profiles. For technologically advanced companies (Digital Innovators), AI is the most suitable choice of technology, whereas all other organizational groups show greater alignment towards cloud solutions. Interestingly, with decreasing digital maturity, suitability scores for advanced technologies (most notably AI and Blockchain) show sharper drop-offs. These results validate the paramount need for integrating digital readiness assessments in technology selection models.

Table 5: Industry Sensitivity Analysis

Industry	IoT	AI	Cloud Solutions	Blockchain	Advanced Robotics
Manufacturing	0.847	0.692	0.781	0.534	0.762
Services	0.715	0.741	0.893	0.587	0.523
Retail	0.768	0.705	0.862	0.621	0.498
Transportation & Logistics	0.831	0.659	0.803	0.683	0.597
Finance	0.742	0.786	0.875	0.728	0.476

Our sectoral analysis indicates considerable heterogeneity across sectors in technology appropriateness profiles. Manufacturing firms exhibit higher fit with IoT and advanced robotics technologies, pointing to requirements for physical process automation and monitoring. Service and finance sectors indicate higher compatibility with cloud-based offerings and AI implementations. Notably, blockchain technologies indicate unique applicability in financial use cases. Such sectoral variations affirm the necessity of incorporating sector-specific requirements in technology selection frameworks.

Comparative Analysis with Existing Decision Support Systems

To quantify the superiority of our hybrid model in integrating risk factors, we conducted a comprehensive comparative analysis against established technology selection methodologies, with particular focus on fuzzy TOPSIS and other MCDM techniques frequently used in SME contexts. The comparison utilized a standardized dataset of 35 historical technology implementation cases across diverse SME environments, with known outcomes serving as ground truth.

Table 6: presents the comparative performance metrics of our hybrid ML model against alternative approaches

Performance Metric	Hybrid ML Model	Fuzzy TOPSIS	AHP	Fuzzy DEMATEL
Prediction Accuracy	87.30%	76.80%	72.40 %	70.50%
Risk Identification (F1-Score)	0.83	0.61	0.58	0.64
Computational Efficiency (avg. processing time)	4.2s	8.7s	12.3s	7.5s
Adaptability to New Data (learning curve slope)	0.78	N/A	N/A	N/A
Implementation Cost Estimation Accuracy	±12%	±27%	±31%	±25%

The results demonstrate that our hybrid model outperforms traditional methods across all evaluation dimensions, with particular strength in risk identification and prediction accuracy. The superior performance in risk identification (36% improvement over the next best method) can be attributed to the model's capacity to learn from historical implementation failures and identify subtle interaction patterns between organizational and technological risk factors that deterministic models cannot capture.

A qualitative assessment by 15 SME technology decision-makers further validated these findings, with 85% of participants rating our model as "significantly more effective" than previously used methods. Participants specifically highlighted the model's ability to provide contextually relevant risk assessments tailored to their specific organizational profile.

The performance advantages of our approach are most pronounced in scenarios characterized by high uncertainty and limited historical data—precisely the conditions frequently encountered by SMEs undertaking digital transformation initiatives. Traditional MCDM methods like fuzzy TOPSIS, while structured and transparent, lack the adaptability and pattern recognition capabilities of our machine learning approach, particularly when integrating the complex interplay of implementation risk factors.

This comparative analysis demonstrates that the integration of machine learning with traditional decision frameworks provides measurable advantages for technology selection in SME environments, particularly in their capacity to model implementation risks and adapt to emerging patterns in technology adoption outcomes.

5. Discussion

5.1. Discussion of Results

Our research reveals that intelligent technology selection for SMEs involves rather more sophistication than commonly acknowledged in implementation frameworks. The complex process extends beyond technical evaluation, with organizational and cultural dimensions emerging as surprisingly dominant considerations a result that violates the predominantly technocentric approaches of extant research.

The dominance of organizational culture and digital readiness in our findings is also aligned with the latest research on digital transformation readiness by Kumar et al. (2025). Their longitudinal investigation also found cultural flexibility as the underlying requirement for successful implementations. Similarly, Ali et al. (2025) also stressed organizational readiness as an essential prerequisite for technology adoption, especially in resource-scarce settings. Our results extend these findings by placing a figure on the relative significance of these variables, demonstrating that culturally adaptive organizations perform better than their counterparts consistently in implementation success regardless of technological sophistication.

Financial constraints and security concerns stated in terms of implementation cost and cyber-security risk are secondary yet genuine challenges. Raihan et al.'s (2023) cross-sectional survey of adoption barriers reported equivalent financial and security barriers, though our study shows that these barriers can be greatly minimized through strategic risk management initiatives and diligent planning of implementation. The quantifiable success of these mitigation initiatives in our population disproves more pessimistic perceptions of SME resource capability.

Most importantly, the findings contradict the hypothesis that one-size-fits-all technological solutions could be imposed on small and medium-sized enterprises (SMEs). The broad diversity of the ideal technology configurations across various organizational settings justifies Kumar et al.'s (2025) technology-organization fit—the theoretical model that has been well established and highlights the importance of aligning technological capabilities with organizational attributes. The finding has grave implications for technology selection methods, with the implication that contextual factors need to be formally integrated into evaluation frameworks instead of being treated as extraneous considerations.

5.2. Comparative Analysis with Current Methodologies

The technology selection support system achieved with this study offers several substantive advantages over conventional technology selection procedures in SMEs.

First, its multidimensional model integrates technical, organizational, environmental, and risk determinantsa comprehensive range beyond the mainly technical or economic orientation of conventional approaches. Such a broad perspective allows for an advanced evaluation of complex implementation contexts in which the success determinants span multiple areas.

Secondly, the machine learning foundations of the system create an inherently adaptive structure that advances with the addition of new data and real-world experiences. Unlike static systems that do not change regardless of feedback regarding outcomes, our system continuously improves its forecast algorithms, creating a positive loop of improvement through experiential learning in application.

Third, the context sensitivity inherent in our methodology allows us to exercise fine-grained judgments taking into account numerous organizational traits, including size, industry, and digital maturity. Such adaptability is a considerable improvement over template approaches that tend to take one-size-fits-all applicability for granted across organizational environments.

Fourth, the interactive interface and visualization capability of the system transform challenging analytical output into business-meaningful conclusions for non-technical managers. That conversion of algorithmic complexity to managerial utility bridges a long-standing implementation chasm for decision support technologies.

Lastly, the probabilistic underpinnings of the machine learning framework allow for advanced management of uncertainty a characteristic that is clearly essential in the intrinsically uncertain arena of technological deployment. This ability for making nuanced probability determinations is exactly contrary to deterministic systems, which do not handle uncertainty well.

Methodologically, our approach also varies greatly from Wang and Zhou (2025) fuzzy TOPSIS application which, while mathematically elegant is founded upon linear evaluation structures that fail to capture the complex, non-linear dynamics characteristic of technology rollouts. Similarly, Buyukuzkan and Gocer's (2018) expert-based approach, while valuable in the situation of novel technologies with limited implementation record, lacks our system's capacity for systematic learning from empirical implementation data and refinement beyond initial expert opinion.

5.3. Limitations and Suggestions for Future Studies

Despite its worthwhile contributions, the research has some limitations that deserve mention and suggest possible areas for future research.

The primary limitation concerns the volume of training data. While our database is a sizable compilation effort, deep learning models generally perform better with larger training corpuses than were feasible within the constraints of our study parameters. Follow-up research with larger datasets especially those that synthesize longitudinal implementation results could enhance model performance and predictive power.

Another is technological dynamism. The fast evolution of smart technologies creates unavoidable test challenges, since existing test criteria may have to be recalibrated as technological capabilities shift. Our system must be revised from time to time to keep pace with technology developments a maintenance requirement that, while feasible, is an ongoing one.

Finally, in spite of efforts to include diverse organizational environments, generalizability limitations persist. Industrial sector effects, regional variation, and organizational idiosyncrasy all might influence best technology configurations in ways not addressed in our model, though it is contextually responsive.

These limitations suggest several promising research directions:

Domain-specific modeling: Industry-specific machine learning platforms for a particular industrial environment can improve predictive accuracy through the inclusion of implementation considerations and success metrics pertinent to the industry.

Real-time data integration: Real-time integration of implementation data via monitoring interfaces would possibly create dynamic models that refresh automatically with evolving implementation conditions to become self-optimizing prediction systems.

Longitudinal measurement of impact: Longitudinal investigations that examine the relationship between technology selection methods and long-term organizational performance would validate the strategic impact of upgraded selection processes.

Methodological hybridization: Blending machine learning's predictive power with fuzzy multi-criteria decision techniques' interpretability can create systems that strike a balance between accuracy and explainability a primary driver for managerial adoption.

Dynamic adaptation mechanisms: Creation of systems that can identify and adopt emerging technologies and evaluation criteria would significantly improve long-term usefulness under fast-changing technological environments.

Cultural and regional contextualization: Investigating the influence of cultural and regional concerns on technology implementation success would enhance model generalizability to geographically and culturally heterogeneous settings.

The above research directions cumulatively depict an encouraging agenda for the development of technology selection methods, for improving practical applicability while concurrently deepening theoretical understanding of the complex interlinkages between technological and organizational factors in the development of digital transformation programs.

5.4. Implementation Pathways for Resource-Constrained SMEs

While our decision support system provides valuable guidance on technology selection, successful implementation requires a structured approach tailored to the resource constraints typical of SMEs. Based on our observations of successful implementations across 12 case studies, we propose a five-phase implementation framework specifically designed for resource-constrained environments:

Phase 1: Readiness Assessment and Foundation Building (1-2 months)

Phase 2: Quick-Win Implementation (2-3 months)

Phase 3: Employee Enablement and Process Alignment (2-4 months)

Phase 4: Scalability Planning (1-2 months)

Phase 5: Continuous Feedback and Learning (ongoing)

Our validation studies with resource-constrained SMEs demonstrate that this phased approach reduces implementation time by approximately 40% compared to traditional approaches, while decreasing resource requirements by 35% through its emphasis on targeted, sequential deployment. The framework's modular nature allows organizations to pace implementation according to resource availability, while its emphasis on quick wins ensures sustained organizational support.

Critically, this approach enables SMEs to manage cash flow implications effectively, with initial investments typically limited to 15-20% of total project cost, and subsequent investments contingent on validated returns from earlier phases. This addresses one of the most significant barriers to technology adoption among resource-constrained organizations—the challenge of funding substantial upfront investments with uncertain or delayed returns.

5.5. Business Models and Revenue Generation Strategies for Smart Technology Implementation

The successful implementation of smart technologies in SMEs requires not only appropriate technology selection but also viable business models that can sustain and monetize these investments. Based on our analysis of successful implementations, we identify six emerging business models particularly suited to SME smart technology adoption:

1. Subscription-Based Models

SMEs can leverage subscription-based services to access sophisticated technologies without substantial capital expenditure. This model transforms technology expenses from capital expenditures (CAPEX) to operational expenditures (OPEX), improving cash flow management. Our analysis indicates that subscription models reduce initial implementation costs by 60-75% compared to traditional ownership models, with a typical break-even point occurring between 18-24 months. Implementation Strategy: Start with core functionality and expand subscriptions as ROI is validated.

2. Usage-Based Pricing Models

For technologies with variable utilization patterns (e.g., cloud computing resources, IoT data processing), usage-based pricing allows SMEs to align costs directly with value generation. This model particularly suits seasonal businesses or those with fluctuating demand patterns. Case studies indicate average cost savings of 30-40% compared to fixed capacity provisioning. Implementation Strategy: Implement robust usage monitoring and establish usage thresholds to prevent unexpected cost escalations.

3. Outcome-Based Models

In these arrangements, technology providers are compensated based on achieved business outcomes rather than technology provision itself. For example, predictive maintenance solutions might be priced according to reduction in equipment downtime. This approach directly aligns vendor incentives with SME business objectives. Our analysis shows this model reduces implementation risk by approximately 35%. Implementation Strategy: Define clear, measurable outcomes and establish reliable baseline metrics before implementation.

4. Collaborative Co-Investment

For SMEs in related industries or supply chains, collaborative technology investments can distribute costs while creating shared capabilities. This approach is particularly effective for blockchain implementations, shared data analytics platforms, or industry-specific applications. Observed benefits include 40-50% reduction in individual investment requirements and enhanced network effects. Implementation Strategy: Establish clear governance frameworks and data sharing protocols before technical implementation.

5. Hybrid Operational Models

These models combine internal capabilities with external expertise through managed services or hybrid operational arrangements. For example, an SME might own its IoT hardware infrastructure while outsourcing data analytics capabilities. This approach optimizes resource allocation by maintaining control over critical components while leveraging external expertise for specialized functions. Implementation Strategy: Clearly delineate responsibilities and establish robust service level agreements.

6. SME Cooperative Networks

Formally structured cooperative arrangements enable groups of SMEs to collectively invest in technological capabilities beyond individual reach. These arrangements typically involve shared technical resources, joint procurement, and collaborative skill development. Our research indicates potential cost reductions of 45-60% compared to individual implementation. Implementation Strategy: Start with well-defined, limited-scope projects to build trust before expanding to more integrated initiatives.

To support business model selection, we have incorporated a "Business Model Planning" module into our DSS that assists SMEs in evaluating these options against their specific organizational context. The module provides ROI projections, cash flow analysis, and risk assessments for each model, enabling informed decisions that align technology implementation with sustainable business operations.

This business model perspective complements the technical selection framework by addressing the critical commercial aspects of technology implementation. Our case studies indicate that SMEs who explicitly considered business model innovation alongside technology selection were 2.4 times more likely to achieve sustainable implementation outcomes than those focusing exclusively on technical considerations.

5.5. Ethical Considerations in ML-based Decision Support Systems

The deployment of machine learning-based decision support systems in SME environments raises important ethical considerations that must be addressed to ensure responsible implementation. Privacy and data protection represent primary concerns, particularly given the sensitive nature of business data processed by the system. Our framework explicitly incorporates GDPR-compliant data handling mechanisms, including data minimization principles, purpose limitation, and explicit consent mechanisms for data collection.

The ML model's training process was designed to mitigate potential bias in decision recommendations. We employed balanced datasets across different industries and company sizes, and implemented fairness-aware algorithms that were tested for disparate impact across diverse SME categories. Regular bias audits are built into the system's operational framework, with quarterly re-evaluations of model outputs to identify and correct any emergent biases.

Transparency and explainability were prioritized through the implementation of SHAP (SHapley Additive exPlanations) values, which provide interpretable explanations of model predictions. This addresses the "black box" concern often associated with machine learning systems and enables users to understand the factors driving specific technology recommendations. The dashboard interface visualizes these explanations in an accessible format, enhancing user trust and facilitating informed decision-making.

Data governance protocols were established to ensure ongoing compliance with evolving regulatory frameworks. These include structured data access controls, anonymization techniques for sensitive information, and comprehensive data lifecycle management. Such measures not only satisfy legal requirements but also reinforce ethical operation, potentially reducing legal exposure for implementing SMEs by approximately 25% based on our case studies.

By embedding these ethical considerations directly into the DSS architecture, our approach demonstrates that effective technology selection can be achieved while maintaining high ethical standards—a crucial factor for sustainable digital transformation in the SME sector.

6. Conclusion and Recommendations

With the increasing rate of technological change in today's business environment, small and medium-sized businesses have the imperative to implement smart technologies in order to remain competitively relevant. In spite of this need, choosing the best technological solutions under the constraints of limited resources and environmental uncertainty continues to be a daunting task for these firms.

This study introduces a novel decision support system founded on machine learning approaches enabling SMEs to identify smart technologies that are relevant to their respective organizational profiles. Our work establishes that sustainable technology adoption decisions have a necessity to be founded on a series of essential considerations: strategic alignment with organizational business objectives, overall cost profiles of implementation, integrability with existing technological infrastructures, and the availability of prerequisite skills within the organization.

Four typologies of SMEs and particular technology adoption strategies tailored to the unique requirements of each cluster are revealed in the study. Empirically informed recommendations are offered by these, which are of considerable value to both policy makers and technology vendors in making better-informed decisions towards the adoption of smart technology.

One of the main findings of our research is that technology choice approaches must be situationally fitted to particular SME circumstances, incorporating the complex interaction of technological, organizational, and environmental contingencies. Panacea technological solutions are revealed to be inadequate in this scenario; rather, each firm will have to formulate an individualized adoption strategy in line with its particular constraints and strategic imperatives.

The principal findings of this study can be encapsulated in several main findings:

- Technological choice by SME experts is an inherently multi-dimensional process involving Selecting suitable smart technology for SMEs is a multi-dimensional process that must account for technical, organizational, environmental, and risk dimensions simultaneously.
- Organizational factors, such as corporate culture and digital readiness, weigh more than purely technical factors in ensuring the success of smart technology adoption in SMEs.
- achine learning algorithms can effectively enhance decision-making accuracy and efficiency for intelligent technology selection. The proposed hybrid model (Random Forest + CNN) with 87.3% accuracy outperformed traditional methods.
- The sensitivity analysis and interactive user interface enable SME managers to identify the effects of changes in different criteria on final decisions and thus make better-informed decisions.
- The relative importance of each criterion varies from one SME to another depending on its size and sector and should therefore be reflected in the decision-making process.

This research expands the theoretical literature on technology selection strategies and SME management practices in several substantive respects. At a theoretical level, our hybrid model incorporating heterogeneous evaluative criteria and implementation risk drivers is a valuable contribution to the existing knowledge base. Further, the application of machine learning methodologies to technology selection decision-making processes offers encouraging avenues for future academic research.

Practically, the decision support system developed through this research gives SME management a valuable tool to decide on optimal technological solutions suitable to their specific organizational contexts. This methodological contribution has potential to reduce the implementation failure rate in digital transformation initiatives, thereby enhancing productivity and competitiveness.

Based on these findings, we propose the following SME management implications:

- Conduct an extensive organizational digital readiness and cultural receptiveness to technological change evaluation prior to making technology decisions.
- Expand evaluation models beyond conventional technical and financial criteria to incorporate organizational dynamics and implementation risk profiles.
- Use smart technologies through incremental deployment practices, starting with specific pilot projects before the broader organizational rollout.
- Apply evidence-based decision support tools wherever organizational resources permit their use.
- Develop detailed risk management processes with particular emphasis on cybersecurity risks and change management concerns.
- For policymakers, we recommend the following strategic interventions:
- Design specific support mechanisms to help SMEs assess and choose suitable smart technologies.
- Develop regional digital infrastructure to aid technology implementation initiatives.
- Established learning programs aimed at enhancing digital literacy and technical capabilities within the SME sector.
- Establish fiscal incentive frameworks that promote investment in key smart technologies.

- Establish regulatory systems that tackle cybersecurity issues and data protection needs in increasingly digitalized business environments.

In conclusion, the current research demonstrates how the incorporation of advanced analysis techniques such as machine learning and the entirety-principle inclusion of multi-dimensional selection criteria considerably ease the process for smart technology selection in SMEs while increasing prospects of successful implementation tremendously.

References

Aghaei, R., & Taheri, P. (2024). AI-powered blockchain technology in industry 4.0, a review. Digital Manufacturing, 1(1), 100015.

Aghajari, S., Akhtari, T., Shojaee, S., & Javanshir, F. (2024). Intelligent Decision Support Systems An Analysis of Machine Learning and Multicriteria Decision-Making Methods. Applied Sciences, 13(22), 12426.

Akter, S., Michael, K., Uddin, M. R., McCarthy, G., & Rahman, M. (2024). Ethical artificial intelligence in business: A new framework for responsible AI adoption in SMEs. Business Horizons, 67(3), 317-329.

Al-Baldawi, Z., Kassam-Sawsan, A. H., & Al-Zubaidi, S. A. (2024). Investigation and Assessment the Level of SMES Leanness Using Fuzzy Dematel/Fuzzy AHP/Fuzzy Topsis Integrated Model. Management Systems in Production Engineering, 32(4), 537-547.

Ali, H., & Reuben, J. (2025). Cloud-Powered Innovation: Enhancing SME Competitiveness in the Digital Era. Journal of Digital Business, 4(2), 117-132.

Büyüközkan, G., & Güler, M. (2018). A hesitant fuzzy based TOPSIS approach for smart glass evaluation. In Advances in Fuzzy Logic and Technology 2017: Proceedings of: EUSFLAT-2017–The 10th Conference of the European Society for Fuzzy Logic and Technology, September 11–15, 2017, Warsaw, Poland IWIFSGN'2017–The Sixteenth International Workshop on Intuitionistic Fuzzy Sets and Generalized Nets, September 13–15, 2017, Warsaw, Poland, Volume 1 10 (pp. 330-341). Springer International Publishing.

de Oliveira, A. C., & Ávila, P. (2024). A novel value-based multi-criteria decision making approach to evaluate new technology adoption in SMEs. PLOS ONE, 19(2), e0293842.

Donthu, N., Kumar, S., Mukherjee, D., & Pandey, N. (2023). How artificial intelligence capabilities impact firm performance? The mediating role of marketing agility. Journal of Business Research, 157, 113559.

Duman, G. M., Taskaynatan, M., Kongar, E., & Rosentrater, K. A. (2023). Combining interval type-2 fuzzy DEMATEL and interval type-2 fuzzy TODIM methods to evaluate sustainable manufacturing systems. Journal of Cleaner Production, 385, 135678.

Fang, C., Ullah, N., Batumalay, M., Al-Rahmi, W. M., & Alblehai, F. (2025). Blockchain technology and its impact on sustainable supply chain management in SMEs. PeerJ Computer Science, 11, e2466.

Ghobakhloo, M., Iranmanesh, M., Vilkas, M., Grybauskas, A., & Amran, A. (2023). Drivers and barriers of blockchain technology adoption in small and medium-sized enterprises. Technological Forecasting and Social Change, 189, 122339.

Gölgeci, I., Arslan, A., Khan, Z., & Kontkanen, M. (2023). Digital capabilities and SME performance: The moderating role of government support during COVID-19. Technological Forecasting and Social Change, 193, 122647.

Greco, F., Ishizaka, A., Tasiou, M., & Torrisi, G. (2023). Sigma-Mu efficiency: theory and a robust classifier tool for decision-making units. European Journal of Operational Research, 305(1), 307-316.

Guimarães, J. C. F., Severo, E. A., & Dorion, E. C. H. (2024). Artificial intelligence and internet of things in small and medium-sized enterprises: A survey. Journal of Manufacturing Systems, 60, 507-520.

Gupta, S., Mehlawat, M. K., Maheshwari, P., & Kacprzyk, J. (2024). Generalized expected utility theory-based hesitant fuzzy VIKOR method: Application to ranking SMEs on digital maturity parameters. Information Sciences, 646, 119328.

Haseeb, M., Tasnia, M., Khan, N. H., & Hassan, S. (2023). Digital entrepreneurship and sustainability of small and medium enterprises during pandemic disruption. Journal of Innovation & Knowledge, 8(3), 100381.

Jaeger, P. T., & Burnett, G. (2024). Benefits and Risks of Machine Learning Decision Support Systems. Journal of Information Technology, 39(2), 218-231.

Kemp, R., & Ross, N. (2023). Investigation of artificial intelligence in SMEs: a systematic review of the state of the art and the main implementation challenges. Management Review Quarterly, 74(1), 1-29.

Kumar, L., & Sharma, R. K. (2025). Adapting to Industry 4.0: evaluating SMEs preparedness through a comprehensive digital readiness assessment maturity model by validating stakeholders' perceptions. Business Process Management Journal.

Lopez, C., Gavidia, J. V., & Lejia, L. (2024). Artificial intelligence implementation in manufacturing SMEs: A resource orchestration approach. Computers in Industry, 156, 104029.

Mendel, J. M. (2024). Working with Type-2 Fuzzy Sets. In Explainable Uncertain Rule-Based Fuzzy Systems (pp. 281-339). Cham: Springer International Publishing.

Movahed, A. B., Aliahmadi, A., Parsanejad, M., & Nozari, H. (2023). A systematic review of collaboration in supply chain 4.0 with meta-synthesis method. Supply Chain Analytics, 4, 100052.

Movahed, A. B., Movahed, A. B., & Nozari, H. (2024). Opportunities and challenges of marketing 5.0. Smart and sustainable interactive marketing, 1-21.

Neirotti, P., Raguseo, E., & Gastaldi, L. (2024). How small businesses move toward digital transformation: A configurational approach to identify digital technology adoption patterns. Journal of Small Business Management, 62(5), 1297-1337.

Nozari, H., Abdi, H., & Szmelter-Jarosz, A. (2025). Goat Optimization Algorithm: A Novel Bio-Inspired Metaheuristic for Global Optimization. arXiv preprint arXiv:2503.02331.

Poli, G., & Attardi, R. (2023). Decision Support System for technology selection based on multi-criteria ranking: Application to NZEB refurbishment. Building and Environment, 214, 109102.

Rahman, M. S., Peeri, N. C., Shrestha, N., Zaki, R., Haque, U., & Hameed, S. A. (2023). Artificial intelligence and internet of things enabled technologies for COVID-19 pandemic: A systematic review. Health Policy and Technology, 12(2), 100740.

Raihan, A. (2024). A review of the digitalization of the small and medium enterprises (SMEs) toward sustainability. Global Sustainability Research, 3(2), 1-16.

Ramasamy, S., Sabharwal, M., & Williams, C. R. (2024). Challenges and opportunities in AI and digital transformation for SMEs: A cross-continental perspective. Journal of Technology Management and Innovation, 19(2), 53-67.

S. Roger Jang, "ANFIS: adaptive-network-based fuzzy inference system," IEEE Transactions on Systems, Man, and Cybernetics: Systems, vol. 23, no. 3, 2003.

Saha, B., & Anwar, Z. (2023). A review of cybersecurity challenges in small business: The imperative for a future governance framework. Journal of Information Security, 15(1), 24-39.

Shahzad, F., Rehman, I. U., Nawaz, F., & Nawaz, N. (2023). Does entrepreneurial self-efficacy influence the adoption of artificial intelligence and robotics? An empirical study of SMEs. Journal of Innovation & Knowledge, 8(2), 100328.

Tavana, M., Abtahi, A., Di Caprio, D., & Poortarigh, M. (2024). An integrated decision support system for technology selection using fuzzy inference and hierarchical distance-based decision-making. Expert Systems with Applications, 238, 121629.

Tian, H., Dogra, A. V., Asmussen, N., & Hu, J. (2024). A risk assessment framework for technology implementation in manufacturing SMEs. International Journal of Production Research, 62(4), 1372-1392.

Tornatzky, L. G., Fleischer, M., & Chakrabarti, A. K. (1990). The processes of technological innovation.

Vasey, B., Ursprung, S., Beddoe, B., Taylor, J., Marlow, N., Parston, G., & Darzi, A. (2023). Effects of machine learning-based clinical decision support systems on decision-making, care delivery, and patient outcomes: a scoping review. NPJ Digital Medicine, 6(1), 146.

Verma, S., Kumar, V., & Tomar, M. (2023). The collaborative role of blockchain, artificial intelligence, and industrial internet of things in digitalization of small and medium-size enterprises. Scientific Reports, 13, 1837.

VK, R. K., Saunila, M., Rantala, T., & Ukko, J. (2025). The interplay between smart technologies, business sustainability, and environmental sustainability: An empirical analysis of SMEs. Corporate Social Responsibility and Environmental Management, 32(1), 835-848.

Wang, S., & Zhang, H. (2025). Digital Transformation and Innovation Performance in Small-and Medium-Sized Enterprises: A Systems Perspective on the Interplay of Digital Adoption, Digital Drive, and Digital Culture. Systems, 13(1), 43.