

Balancing intelligence and intuition: a human-AI decision support model for strategic technology adoption in SMEs

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ABSTRACT

This article presents a novel decision-support framework, Hybrid AI-Augmented Decision Optimization (HAI-HDM), designed to accelerate and improve technology adoption in small and medium enterprises (SMEs). HAI-HDM bridges artificial intelligence and human expertise to deliver context-aware, data-driven technology recommendations custom-made to the unique challenges of SMEs. The framework has five core components: data acquisition and preprocessing, artificial intelligence (AI)-powered technology ranking, human-AI decision integration, explainable recommendation generation, and adaptive learning. To support analytical insights, HAI-HDM utilizes machine learning algorithms. For transparency and confidence, it integrates explainable AI (XAI) tools SHapley Additive exPlanations (SHAP) and Local Interpretable Model-agnostic Explanations (LIME), making the foundation behind each recommendation interpretable. A key feature is its dynamic weighting mechanism, which adjusts the stimulus of human judgment and AI confidence based on the degree of vagueness and corporate context. The framework also employs reinforcement learning, leveraging feedback from real-world adoption situations to continuously improve its recommendations. A case study focused on cloud technology adoption establishes the practical effectiveness of HAI-HDM, showing how it aligns technological choices with professional constraints and strategic goals. By combining analytical power with human insight, the framework not only supports informed decision-making but also promotes greater trust and accountability in AI-driven strategic planning.

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INTRODUCTION

Making smart technology choices is tough for small and medium enterprises (SMEs). It requires knowledge to balance what they know, what the data says, and the specific situation they are in. Since SMEs frequently operate with limited resources, effective and precise decision-making is essential for survival and growth, in contrast to

large firms with specialized research and development (R&D) teams and substantial financial resources (Sotamaa, Reiman & Kauppila, 2025; Carayannis et al., 2024, 2025). Fully automated artificial intelligence (AI)-driven decision-making has limitations, even though AI has become an effective tool for optimizing decision-making through the analysis of enormous volumes of data and the identification of trends (Carayannis et al., 2025; Rialti & Zollo, 2023). These include the possibility of algorithmic bias, explainability problems, and a lack of contextual knowledge. However, decision-making that is solely based on human judgment has several drawbacks, including slower data processing, cognitive biases, and a dependence on intuition rather than insights from data.

SMEs are under growing pressure to embrace cutting-edge technologies like cloud computing, AI, blockchain, and Internet of Things (IoT) in order to remain competitive in today's rapidly evolving digital market (Rialti & Zollo, 2023). However, SME leaders frequently face obstacles like:

- ROI uncertainty: A lot of SMEs are hesitant to embrace new technology since the long-term sustainability risks and financial rewards are not entirely evident.
- Lack of experience: SMEs frequently lack internal specialists to assess and apply cutting-edge technologies, in contrast to huge corporations.
- Risk of failure: Inadequate technological adoption decisions might result in large monetary losses and business interruptions.

Traditional frameworks for technology adoption, such the diffusion of innovation (DOI) theory, the technology acceptance model (TAM), and the technology-organization-environment (TOE) framework, offer strong theoretical foundations for comprehending how businesses embrace new technologies (Awa, Ojiabo & Emecheta, 2015). However, these models presume that adoption decisions follow a linear and well-defined process and mostly rely on static decision criteria. They do not take into consideration how dynamic current decision-making is, where real-time data, shifting market situations, and flexible approaches are all essential (Awa, Ojiabo & Emecheta, 2015).

The landscape of AI-driven decision-making has evolved significantly, with growing emphasis on human-AI collaborative frameworks. A recent study by Ahmed & Pardaev (2025) demonstrates that effective AI collaboration requires careful balance between automated recommendations and human oversight, particularly in complex evaluation scenarios. Their research reveals that while AI excels at objective assessments, human expertise remains superior in subjective judgment contexts, supporting the need for hybrid approaches. Similarly, research on human-AI decision dynamics by Liu & Liu (2025) shows that trust in AI, risk propensity, and decision fatigue interact significantly to shape collaborative decision outcomes, emphasizing the importance of adaptive weighting mechanisms that account for human cognitive factors.

Research in reinforcement learning-based decision support systems has shown remarkable progress in adaptive learning capabilities. Zhang et al. (2024) introduced dynamic weight adjustment mechanisms in Deep Q-Networks that enhance real-time

environmental adaptation, demonstrating significant improvements in model responsiveness to changing conditions. This aligns with recent advances in bio-inspired adaptive neural networks by [Islam, Bouzerdoun & Belhaouari \(2024\)](#), which model neuron weights as functions of input signals, enabling dynamic real-time adjustments that parallel biological neural adaptation. The critical importance of explainable AI (XAI) in business applications has gained substantial attention in recent literature. [Vimbi, Shaffi & Mahmud \(2024\)](#) conducted a systematic review of SHapley Additive exPlanations (SHAP) and Local Interpretable Model-agnostic Explanations (LIME) applications, demonstrating that these frameworks significantly enhance model interpretability and user trust, with SHAP providing global understanding while LIME excels in localized insights. Their research shows that combining these approaches can achieve up to 97.6% accuracy in complex diagnostic scenarios while maintaining transparency.

Recent comparative analyses by [Hasan \(2023\)](#) highlight that SHAP's consistency and stability make it particularly suitable for complex business models, while LIME's computational efficiency benefits simpler applications requiring rapid local explanations. The growing regulatory landscape, particularly with the EU's AI Act, has made explainability not just beneficial but legally necessary for business AI implementations. Research by [Grobrügge et al. \(2024\)](#) presents novel methods for assessing agreement between different explainability techniques, providing frameworks for practitioners to select appropriate XAI methods based on their specific business contexts. The 2023 U.S. Chamber of Commerce report reveals that 95% of U.S. small businesses now use at least one technology platform, with AI adoption reaching 24% of SMEs and showing 12-point increases in profit growth likelihood for AI users ([Zamani, 2023](#)). This widespread adoption reflects the critical role of technology in SME competitiveness, particularly in post-pandemic recovery scenarios. A SME study by [Sudirman, Astuty & Aryanto \(2025\)](#) demonstrate that sustainable resilience strategy mediates the relationship between entrepreneurial orientation and digital technology adoption, with entrepreneurial competencies serving as crucial enablers. Their framework shows that SMEs with strong resilience strategies are significantly more likely to successfully implement digital technologies. Similarly, research on women-led SMEs by [Tubastuvi & Purwidiyanti \(2023\)](#) reveals that financial literacy and technology adoption contribute significantly to financial inclusion, with technology serving as a key mediator in performance improvement. European SME digitalization study by [Holl & Rama \(2024\)](#) identifies considerable heterogeneity in advanced digital technology adoption related to local business environments and urban/rural hierarchies, with rural SMEs facing additional barriers despite similar firm characteristics. This spatial analysis reveals that good business environments consistently encourage digital adoption regardless of geographic location.

Furthermore, conventional models are unable to adequately handle the complex nature of AI-driven automation and augmentation as AI becomes more and more integrated into decision-making. Many of these models function as black-box systems, despite the fact that AI-powered decision support systems have several benefits in terms of speed, efficiency, and predictive analytics. Decision-makers become sceptical when AI-generated recommendations lack transparency because they find it difficult to understand the logic

behind them. Despite the potential advantages of AI, adoption is frequently hampered by this opacity, which undermines confidence in AI-powered decision assistance (Sotamaa, Reiman & Kauppila, 2025; Carayannis et al., 2024, 2025).

Existing research has three key limitations that this study addresses: First, current AI-driven decision support systems, while efficient in processing large datasets, fail to account for the contextual nuances and resource constraints that are fundamental to SME decision-making processes. These systems typically operate as black-box models without providing the transparency and explainability that SME leaders require to build trust in technology recommendations. Second, traditional technology adoption frameworks (DOI, TAM, TOE) assume linear, static decision processes and do not incorporate real-time adaptive learning capabilities that can evolve based on actual implementation outcomes and changing business environments, a critical need for resource-constrained SMEs operating in dynamic markets. Third, and most significantly, there is a notable absence of frameworks that systematically integrate human expertise with AI-generated insights through dynamic weighting mechanisms that can adjust based on decision uncertainty and contextual factors specific to SME environments. No existing study has developed a comprehensive model that combines explainable AI techniques with adaptive human-AI collaboration specifically designed for SME technology adoption scenarios.

This research gap is particularly problematic for SMEs because unlike large enterprises with dedicated R&D teams and substantial resources, SMEs require decision support systems that are simultaneously data-driven, contextually aware, transparent, and adaptable to their unique operational constraints and limited technical expertise. The absence of such integrated frameworks leaves SMEs vulnerable to suboptimal technology adoption decisions that can significantly impact their competitiveness and long-term viability.

This study's main goal is to develop and validate Hybrid AI-Augmented Decision Optimization (HAI-HDM) for SMEs' strategic use of technology. The study's specific objectives are to:

- Develop a novel hybrid AI-human decision-making model that best combines human expertise and AI-driven insights for SME technology adoption.
- Integrate arguments based on SHAP and LIME to enhance the interpretability and trustworthiness of AI-generated technology suggestions for SMEs.
- Develop an adaptive decision-weighting system that ensures context-aware, human-in-the-loop decisions by modifying AI influence according to business uncertainty.
- Include a feedback loop that allows AI models to be updated dynamically in response to actual SME adoption success, thereby increasing the accuracy of decisions.

The following research questions are addressed in this article with the aim to accomplish the following objectives:

- RQ1: How can human expertise and AI-driven decision models be successfully combined for SMEs to utilize technology strategically?

- RQ2: What are the main determinants of Human-AI Hybrid Decision Models' effectiveness in SMEs?
- RQ3: How does explainable AI (XAI) increase decision-makers' confidence in suggestions for the deployment of AI-driven technologies?

The remainder of this article is structured as follows: The next section provides a literature review followed by an introduction to the proposed HAI-HDM and algorithm. Example use case, discussion on sensitivity analysis, research implication are presented next, followed by the conclusion and future scope.

LITERATURE REVIEW

Small and medium enterprises (SMEs) represent a foundation of global economic development, playing a vital role in job creation and contributing significantly to GDP growth reportedly accounting for nearly 90% of employment expansion worldwide (*Al Khasawneh et al., 2021*). Despite their economic importance, SMEs have been relatively slow in adopting artificial intelligence (AI) technologies compared to larger corporations. This slower pace has exacerbated disparities in innovation and competitive advantage across market segments. These obstacles are mainly associated with their small scale, which limits their access to financial, technological, and human resources (*OECD, 2021*).

A global survey conducted by McKinsey & Company (*Berruti, Phal & Rougeaux, 2021*) revealed that 67% of business executives reported a noticeable acceleration in the adoption of automation and AI within their organizations. This trend underscores the general impact of AI across industries, affecting operational models and strategic planning at all levels (*Bresciani et al., 2021*). While the academic research on AI and its implications for management and organizational theory dates back several decades (*Haenlein & Kaplan, 2019*), recent technological advancements have made AI increasingly capable of handling complex cognitive tasks traditionally reserved for human decision-makers.

These developments have enabled AI systems to support a wide range of organizational functions, including analytical reasoning, judgement, and strategic decision-making (*Dal Mas et al., 2023; Mahroof, 2019; Von Krogh, 2018*). With the ability to process vast datasets and generate predictive insights, AI equips managers with enhanced decision-making tools, facilitating a more data-driven approach to understanding and responding to emerging business challenges (*Ghasemaghahi, Ebrahimi & Hassanein, 2018*).

This strong evidence on growing advancements in AI particularly in algorithms capable of hierarchical abstraction and big data analytics are instrumental in transforming organizational capabilities (*Giachino et al., 2024*). AI offers a broad spectrum of applications that enable firms to gain strategic advantages, streamline operations, and enhance overall business efficiency particularly through optimized cost structures and improved performance metrics (*Muminova et al., 2024*). For SMEs, leveraging these technological advancements is increasingly becoming essential to maintaining competitiveness in dynamic market environments. Failure to adopt and integrate such innovations may place SMEs at a strategic disadvantage, potentially eroding their market share and long-term viability (*Muminova et al., 2024*). However, while the benefits of AI

are compelling, SMEs face a range of obstacles that can hinder effective adoption. These include limitations in financial resources, technical expertise, infrastructure, and organizational readiness (Bettoni et al., 2021; Oseni et al., 2021). Addressing these challenges is critical for SMEs to fully realize the transformative potential of AI and sustain their competitive positioning in an increasingly digitized business landscape.

AI-driven decision-making models leverage advanced techniques such as machine learning, deep learning, and predictive analytics to generate optimized recommendations based on historical data and evolving market dynamics. By enhancing decision accuracy and operational efficiency, AI provides organizations with clear advantages in effectiveness and objectivity (Sotamaa, Reiman & Kauppila, 2025). Its adoption spans a variety of organizational functions, including marketing, customer service and human resource management, particularly in recruitment and hiring decisions. This integration reflects a collaborative synergy between machine intelligence and human expertise, emphasizing the critical role of human oversight and input in AI-enabled systems (Sotamaa, Reiman & Kauppila, 2025; Carayannis et al., 2024, 2025).

Recent systematic reviews have provided comprehensive insights into the factors influencing technology adoption in SMEs across diverse contexts. A systematic literature review on cloud accounting adoption identifies technological, organizational, and environmental determinants such as relative advantage, top management support, and regulatory pressure that significantly affect SMEs' willingness to migrate financial processes to cloud platforms, while Gupta, Fernandez-Crehuet & Gupta (2022) demonstrate that cloud computing combined with knowledge management substantially enhances software development innovation within organizations. Similarly, Mensah & Xu (2025) presents a survey of e-commerce adoption in SMEs highlights the application of TAM, UTAUT, and TOE frameworks, revealing that contextual adaptations (e.g., industry specificity, regional infrastructure) are often underexplored and recommending more nuanced model refinements to capture SMEs' unique constraints and decision drivers. More recently, Bindeeba, Tukamushaba & Bakashaba (2025) presents a comprehensive review of digital transformation in SMEs synthesizes qualitative and quantitative studies to map common barriers such as limited digital skills, high implementation costs, and cultural resistance and enablers, including leadership commitment, external partnerships, and government support, offering a research agenda for targeted interventions and policy measures to accelerate SME digitalization.

Table 1 summarizes the key challenges faced by both AI-driven and human-driven decision-making processes in the context of technology adoption within SMEs. While AI excels in processing vast datasets efficiently and automating routine decisions, it often struggles with explainability and lacks the nuanced understanding of contextual factors. On the other hand, human decision-makers bring valuable intuition and experience to the table but may be prone to cognitive biases, slower information processing, and inconsistencies.

Table 2 further presents a comparative analysis of AI and human decision-making based on essential criteria such as efficiency, adaptability, transparency, and susceptibility to bias. The findings highlight the necessity of adopting HAI-HDM that

Table 1 Comparison of AI-driven and human-driven decision-making in SME technology adoption.

Challenge	Limitations of AI-driven decision-making	Limitations of human-driven decision-making
Lack of transparency (black-box nature)	Many AI models function as opaque systems, making it difficult for stakeholders to understand the rationale behind specific recommendations, reducing trust and slowing adoption.	—
Over-reliance on historical data	AI systems trained predominantly on historical data may fail to capture emerging trends or abrupt shifts, potentially leading to outdated or suboptimal technology recommendations.	—
Lack of contextual understanding	AI struggles with qualitative factors such as leadership vision, organizational culture, or team readiness. For example, it might suggest automation when a human-centric approach fits better.	While humans incorporate context and intuition, such assessments may be inconsistent or overly influenced by personal experience or subjective interpretation.
Ethical and bias risks	AI can inadvertently propagate data-driven biases, such as recommending enterprise tools that exceed SME budgets, creating ethical concerns.	Human decisions may reflect personal biases or prior preferences, possibly overlooking innovative or cost-effective alternatives.
Cognitive bias influence	—	Decision-makers may exhibit biases like confirmation bias or overconfidence, for instance, clinging to familiar tools despite better modern alternatives.
Processing large volumes of data	AI excels at rapid, large-scale data analysis, enabling pattern recognition and insight generation across complex datasets.	Humans may find it difficult to handle and interpret extensive data manually, resulting in slower or less informed decisions.
Limited awareness of emerging technologies	AI systems regularly update based on new data, offering insights aligned with current industry developments.	Many SMEs lack access to up-to-date tech insights, making adoption reactive rather than strategic. An example includes avoiding AI-based security due to lack of awareness or training.
Consistency vs. emotional variability	AI maintains uniformity in decision-making, unaffected by fatigue, emotions, or interpersonal dynamics.	Human decisions can vary with mood, stress levels, or internal resistance, potentially leading to inconsistent or emotionally influenced choices.

combines the analytical rigor of AI with the judgment and contextual awareness of human decision-makers. Such a hybrid approach promises to support SMEs in making more informed, flexible, and balanced technology adoption choices, ultimately improving organizational outcomes.

Existing decision-making frameworks often treat AI-driven and human approaches as separate, isolated processes rather than integrated components. This division creates a significant challenge for small and medium enterprises (SMEs) in their efforts to adopt new technologies effectively. Specifically:

- AI-based models provide valuable efficiencies and data-driven insights but are limited by a lack of intuition, flexibility, and transparency in their decision logic.
- Human decision-makers contribute essential experience and contextual judgment but are vulnerable to cognitive biases, inconsistency, and slower information processing.
- To date, there is no widely accepted or comprehensive framework that successfully combines human expertise with AI-generated recommendations in a way that ensures balanced, transparent, and adaptable decision-making tailored to the needs of SMEs.

Table 2 Gap in SME technology adoption: AI vs. human decision-making.

Decision-making factor	AI-driven models	Human decision-making
Efficiency & DATA-BACKED insights	High–Capable of processing large volumes of data rapidly, offering data-driven insights for decision-making.	Limited–Relies more on manual analysis and intuition, making it slower and less data-oriented.
Intuition & contextual awareness	Lacking–Struggles to understand qualitative factors like organizational culture, leadership style, or stakeholder sentiment.	Strong–Leverages human experience, domain understanding, and contextual judgment.
Explainability & transparency	Low–Often functions as a black box, making it difficult to interpret or justify outcomes.	High–Human reasoning is generally explainable, enabling clearer communication of decisions.
Adaptability to market changes	Rigid–Dependent on past data and fixed algorithms, making it less responsive to sudden shifts.	Flexible–Can pivot quickly in response to evolving market conditions or strategic shifts.
Bias & subjectivity	Risk–May carry hidden biases from training data, affecting fairness and objectivity.	Present–Subject to personal biases, emotions, or past experiences, which may affect neutrality.

This research proposes the HAI-HDM to bridge this gap by leveraging the strengths of both AI and human decision-makers, ensuring SMEs can make strategic, data-driven, yet context-aware technology adoption decisions.

PROPOSED APPROACH: HUMAN-AI HYBRID DECISION MODEL (HAI-HDM)

This article presents HAI-HDM, a strategic framework aimed at supporting technology adoption decisions within SMEs. By integrating advanced machine learning and reinforcement learning techniques, the model delivers intelligent, data-driven recommendations tailored to the unique needs of SMEs. To build trust and ensure transparency, the model incorporates XAI methods such as SHAP and LIME, helping stakeholders understand the reasoning behind each recommendation. [Figure 1](#) depicts human-AI hybrid decision model.

A key innovation in HAI-HDM is its adaptive AI-human weighting mechanism, which dynamically balances AI insights and human judgment based on the specific decision context and uncertainty levels. This ensures that while AI enhances analytical rigor, human expertise remains central to the final decision. Furthermore, the framework includes a continuous learning and feedback loop that allows the system to evolve by learning from real-world adoption outcomes and expert feedback making the decision-making process not only more transparent but also increasingly adaptive and effective over time.

The HAI-HDM framework is built upon four interconnected components that collectively enable intelligent, transparent, and adaptive technology decision-making for SMEs:

(1) Data collection and preprocessing

This module gathers both structured and unstructured data from diverse sources including market trends, SME case studies, financial statements, and industry benchmarks. To extract meaningful insights from qualitative sources such as SME

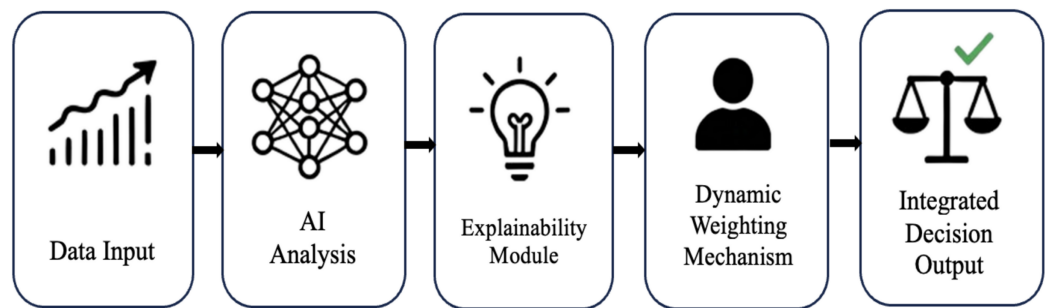


Figure 1 Human-AI hybrid decision model.

Full-size DOI: [10.7717/peerj-cs.3341/fig-1](https://doi.org/10.7717/peerj-cs.3341/fig-1)

reports and narrative business decisions the system uses advanced natural language processing (NLP) techniques. This helps transform raw information into actionable data that feeds into the recommendation engine.

(2) AI-based technology recommendation system with explainability

At the core of the framework is an AI-powered recommendation engine that employs models like Random Forest, extreme gradient boosting (XGBoost), and deep neural networks to predict the most suitable technologies for a given SME context. To ensure these recommendations are not only accurate but also trustworthy, the explainability module integrates SHAP and LIME, two leading explainable AI tools that offer clear, interpretable justifications for the system's predictions. Furthermore, reinforcement learning (RL) is used to fine-tune the recommendations based on real-world adoption trends, allowing the system to improve over time.

(3) Human-AI decision fusion mechanism

This component introduces a thoughtful balance between human judgment and AI suggestions through two key metrics: the AI confidence score (AICS), which reflects how confident the system is in its recommendation, and the human expertise score (HES), which captures factors such as decision-maker trust, perceived risk, and SME-specific constraints. A dynamic weighting mechanism intelligently adjusts the decision-making balance favoring AI in situations with low uncertainty and giving humans more control in complex or high-stakes scenarios.

(4) Feedback and continuous learning

To ensure ongoing improvement, this module integrates human feedback and real-world outcomes from SME technology adoption. Through reinforcement learning, the system rewards successful decisions and adjusts future recommendations accordingly. This continuous learning cycle helps refine the model's confidence and recommendation strategies, making the decision process smarter, more adaptive, and aligned with evolving business realities.

ALGORITHM

The decision-making process begins with data collection and pre-processing, where both structured and unstructured data such as market trends, financial reports, and previous

Algorithm.

Input

$T = \{T_1, T_2, \dots, T_n\} \rightarrow$ Technology options
 $C = \{C_1, C_2, \dots, C_m\} \rightarrow$ Business constraints (budget, security, scalability)
 $D = \{D_1, D_2, \dots, D_p\} \rightarrow$ Historical adoption data
 $H = \{H_1, H_2, \dots, H_q\} \rightarrow$ Human expertise & feedback
 $\theta \rightarrow$ AI confidence threshold

Output

$T^* \rightarrow$ Optimal technology selection
 FUNCTION HAI-HDM_ALGORITHM (T, C, D, H, θ):
 # Step 1: Data Collection & Preprocessing
 Data $\leftarrow$ Collect_Data_Sources(T, C, D)
 Features $\leftarrow$ Extract_Features(Data)
 Normalized_Data $\leftarrow$ Normalize(Features)
 # Step 2: AI-Based Technology Recommendation
 Model $\leftarrow$ Train_AI_Model(Normalized_Data)
 IF Classification_Problem:
 # Compute technology adoption probability
 AI_Scores $\leftarrow$ Model.Predict_Probabilities(T)
 ELSE IF Clustering_Problem:
 # Group technologies based on adoption similarity
 AI_Scores $\leftarrow$ Cluster_Technologies(T)
 # AI-based confidence score
 FOR each technology T_i in T:
 $S_{AI}(T_i) \leftarrow$ Compute_AI_Confidence(T_i , AI_Scores)
 # Use SHAP for explainability
 Explainability_Report[T_i] $\leftarrow$ Generate_XAI_Justification(T_i)
 # Step 3: Human Expertise & Contextual Adjustment
 FOR each technology T_i in T:
 # Human decision-maker adjustments
 $S_H(T_i) \leftarrow$ Get_Human_Score(H, T_i)
 # Adjust AI-human influence based on uncertainty level
 $\alpha \leftarrow$ Dynamic_Weighting(T_i)
 # Final decision score
 $S_{Final}(T_i) \leftarrow \alpha * S_{AI}(T_i) + (1 - \alpha) * S_H(T_i)$
 # Step 4: Decision Finalization & Implementation
 $T^* \leftarrow$ Select_Optimal_Technology(S_{Final}) # Technology with highest final score
 # AI and human decision justification

(continued)

```
Decision_Report ← Generate_Explainability_Report(T*)
# Define implementation KPIs
Roadmap ← Develop_Adoption_Strategy(T*)
# Step 5: Continuous Learning & Feedback Loop
Monitor_Adoption(T*)
Update_Model(T*, Feedback)
RETURN T*, Decision_Report, Roadmap
END FUNCTION
```

technology adoption cases are gathered and standardized. Next, an AI-based recommendation engine is trained using classification models like Random Forest, XGBoost to estimate the likelihood of successful technology adoption. In addition, clustering techniques such as K-Means is used to uncover hidden adoption patterns across SMEs, offering deeper contextual insights. Once the AI generates its recommendations, it assigns an AICS, representing the model's confidence in each prediction. This score is enhanced using explainable AI techniques like SHAP, which provide transparent, easy-to-understand justifications behind each suggestion. In the human-AI decision fusion stage, SME experts step in to add qualitative insights. Their input contributes to the creation of a HES, reflecting factors like strategic fit, perceived risk, and organizational feasibility. A dynamic weighting mechanism then balances the influence of AI and human input, adapting based on the level of uncertainty in each decision scenario. Lower-risk decisions may rely more heavily on AI, while high-risk or complex cases lean more on human judgment.

The final technology recommendation is chosen based on the combined AI-human weighted score and is supported by a structured implementation roadmap to guide SMEs through adoption. To ensure the model remains effective over time, a continuous learning feedback loop is integrated. Reinforcement learning is used to update the system's predictions based on actual adoption outcomes, allowing the model to adapt, learn from experience, and make increasingly accurate recommendations for future SME technology decisions.

EXAMPLE USE CASE: APPLICATION PROPOSED HAI-HDM ALGORITHM IN SME CLOUD ADOPTION

In this use case, the HAI-HDM framework is applied to guide a manufacturing SME through the cloud adoption process. The system first collects and pre-processes relevant internal data (such as current IT infrastructure and financials) and external data (such as case studies and market benchmarks). AI models trained on historical cloud adoption cases rank potential cloud technologies (e.g., SaaS, IaaS, PaaS) based on performance, cost, and success probability. Explainable AI techniques like SHAP are used to make these rankings transparent. Human experts from the SME then adjust rankings based on organizational context, such as data sensitivity or compliance requirements. Finally, the AI and human

Table 3 Cloud vendor AI scores.

Cloud vendor	AI score S_{AI}
Azure	0.89
AWS	0.85
GCP	0.78
Oracle	0.65
IBM	0.60

scores are dynamically fused to recommend the optimal cloud solution, accompanied by a clear justification and a phased adoption roadmap. The system continues learning from feedback post-implementation, improving its recommendations over time.

In order to illustrate the practical utility of the proposed HAI-HDM framework, a case of a mid-sized retail SME, hereafter referred to as *RetailABC*, evaluating cloud service providers for infrastructure migration. This decision involves multiple, often conflicting, criteria such as cost, scalability, regulatory compliance, and post-deployment support factors which SMEs typically struggle to evaluate due to limited internal technical expertise and decision-making resources. *RetailABC* must choose among five prominent cloud vendors: AWS, Microsoft Azure, Google Cloud Platform (GCP), Oracle Cloud, and IBM Cloud. The company outlines specific constraints, including a monthly budget ceiling of \$10,000, General Data Protection Regulation (GDPR) compliance, and the requirement for multi-region availability with auto-scaling capabilities. Data from 20 SMEs in similar industries is used to train the AI model, capturing adoption success rates, performance metrics, and cost-effectiveness. To ensure representativeness, data from twenty SMEs in similar industries were selected using a stratified random sampling approach across three industry sectors and two size categories (micro: fewer than 10 employees; medium: 50–250 employees). Participating firms spanned a range of ages (3–20 years) and annual revenues (USD 0.1–5 million), and their digital maturity levels were assessed *via* a pre-interview survey. These data were used to train the AI model, capturing adoption success rates, performance metrics, and cost-effectiveness. Additionally, expert insights are incorporated: the CTO emphasizes data integration ease, the IT Manager prioritizes support services, and a consultant focuses on strategic alignment with the firm’s long-term digital roadmap.

A supervised learning model (*e.g.*, Random Forest and XGBoost) trained on historical data produces a preliminary AI-driven score $S_{AI}(T_i)$ for each provider. SHAP is employed to generate local and global explanations, thereby enhancing transparency and trust in the model’s output. For instance, SHAP analysis reveals that Azure’s favorable AI score is largely driven by its competitive pricing and consistently high adoption success across peer SMEs. Table 3 presents $S_{AI}(T_i)$ scores.

Stakeholder evaluations contribute to an adjusted score $S_H(T_i)$ based on qualitative assessments and organizational priorities. These human-influenced scores reflect practical, context-specific concerns not captured by the algorithm. Table 4 presents the $S_H(T_i)$ scores values.

Table 4 Cloud vendor and weighted human score values.

Cloud vendor	SH(T _i) (weighted human score)
Azure	0.87
AWS	0.83
GCP	0.75
Oracle	0.62
IBM	0.58

Table 5 Final score values.

Vendor	AI score S _{AI} (T _i)	Human score S _H (T _i)	Final score S _{Final} (T _i)
Azure	0.89	0.87	0.882
AWS	0.85	0.83	0.846
GCP	0.78	0.75	0.768
Oracle	0.65	0.62	0.638
IBM	0.60	0.58	0.592

Table 6 Results of sensitivity analysis.

α	AWS	Azure	GCP	Oracle	IBM	Selected cloud provider
0.0	0.72	0.80	0.76	0.82	0.79	Oracle
0.2	0.76	0.82	0.778	0.80	0.782	Azure
0.4	0.80	0.84	0.796	0.788	0.774	Azure
0.5	0.82	0.845	0.805	0.783	0.765	Azure
0.6	0.844	0.85	0.814	0.778	0.756	Azure
0.8	0.872	0.86	0.832	0.766	0.738	AWS
1.0	0.88	0.85	0.83	0.78	0.75	AWS

The final decision score S_{Final} is computed using a weighted average of the AI and human scores, with a tunable coefficient $\alpha = 0.6$:

$$S_{\text{Final}}(T_i) = \alpha \times S_{\text{AI}}(T_i) + (1 - \alpha) \times S_{\text{H}}(T_i). \quad (1)$$

Table 5 below presents the final score values.

Accordingly, Azure is selected as the optimal solution due to its balanced performance across cost, support, compliance, and stakeholder satisfaction.

SENSITIVITY ANALYSIS

To evaluate the influence of the AI-human weighting factor, we perform a sensitivity analysis by varying α from 0.0 (human-driven) to 1.0 (AI-driven). Table 6 presents results of sensitivity analysis with varying α .

The sensitivity analysis conducted by varying the weight parameter α , which balances AI recommendations and human judgment, offers valuable insights into the robustness and flexibility of the proposed HAI-HDM. This parameter allows the model to adapt its

reliance on machine intelligence *vs.* expert input, reflecting different organizational preferences and decision-making styles. When α shifts from 0 (purely human-driven decisions) to 1 (fully AI-driven decisions), the ranking of cloud service providers smoothly adjusts, demonstrating that the framework can accommodate a wide spectrum of decision dynamics. The baseline setting of $\alpha = 0.6$, slightly favoring AI, reflects a practical balance where data-driven insights guide the decision while expert knowledge refines it. This combination mirrors real-world SME scenarios, where human expertise complements automated analytics rather than being replaced by it.

Notably, Azure consistently ranks highest regardless of the value of α . This consistent performance arises from its strong AI-based evaluation highlighting its technical merits, cost efficiency, and successful adoption history and from human evaluations emphasizing its data integration capabilities and compliance readiness. This agreement between AI predictions and human priorities reinforces the trustworthiness of the model's recommendations. Other vendors, like AWS and GCP, show moderate sensitivity to the weighting factor. Their rankings improve as the AI's influence grows, indicating that the AI model recognizes their technical strengths more than some stakeholders might. Conversely, Oracle and IBM remain less preferred across all settings, suggesting a shared perception of their limited fit for this SME's specific needs. This alignment between AI outputs and human perspectives enhances the overall decision confidence. From a practical standpoint, these findings suggest that SMEs can tune the α parameter to reflect their own decision-making context. Organizations with less technical expertise may benefit from leaning more heavily on AI-driven recommendations, enabling data-informed choices even when expert resources are limited. On the other hand, SMEs that prioritize strategic, regulatory, or contextual nuances may choose to weigh human judgment more, ensuring that qualitative factors influence the final decision.

Furthermore, the smooth progression of vendor scores across varying α values signals the system's potential for continuous learning and adaptation. As SMEs gather real-world feedback after implementation, the model can recalibrate its balance between AI and human inputs, evolving alongside user trust and experience. Thus, it can be seen that sensitivity analysis highlights the strength of the HAI-HDM framework in delivering transparent, adaptive, and context-sensitive technology adoption guidance.

RESEARCH IMPLICATION

The proposed Human-AI Hybrid Decision-Making framework presents a novel and pragmatic solution for complex decision scenarios in small and medium-sized enterprises (SMEs), especially those navigating technology adoption. The integration of human judgment with explainable AI-based scoring systems allows for more inclusive, context-aware, and balanced decision-making. This section discusses the broader implications of this approach from academic, practical, and policy perspectives.

Traditional decision models often struggle to account for subjective knowledge, tacit understanding, and situational context elements that are critical in SME environments. By incorporating human stakeholder evaluations alongside AI-derived scores, the proposed HAI-HDM framework successfully bridges this gap. This dual-layered evaluation ensures

that decisions are not just analytically sound but also practically grounded in organizational realities. The framework allows for the structured inclusion of diverse stakeholder perspectives ranging from CTOs to operational managers each weighted according to their relevance to the decision context. This promotes transparency and shared ownership in the decision-making process, which is particularly vital in SMEs where collaboration and resource alignment are crucial for implementation success.

By offering a tuneable control over the influence of human *vs.* AI judgment (*via* the α parameter), the approach fosters trust and interpretability in AI-assisted decisions. The sensitivity analysis shows how decision outcomes can be adjusted based on stakeholder preference for human expertise or data-driven objectivity. This flexibility makes the system adaptable across organizational cultures with varying levels of digital maturity. SMEs often operate under resource constraints and face unique business challenges. The HAI-HDM approach, with its ability to factor in strategic, operational, and technical priorities, aligns technology decisions with SME-specific goals. This makes the framework particularly valuable in environments where one-size-fits-all recommendations from generic models are inadequate.

This research contributes to the growing body of work on human-in-the-loop and human-centric AI systems by offering a practical framework that blends explainability, stakeholder participation, and adaptive intelligence. It also sets the stage for future research in areas such as continuous learning, reinforcement from post-adoption outcomes, and integration of emotional or behavioral signals into decision logic. At a broader level, the proposed framework can inform policy-makers and technology providers about the importance of stakeholder-aligned, adaptive decision tools for SMEs. This can guide the development of standards, funding models, and digital adoption roadmaps that better reflect the needs and realities of smaller enterprises.

ETHICAL CONSIDERATIONS

Ethical safeguards are vital when building human-AI decision support systems for SME technology adoption. Safeguarding data privacy is paramount, requiring compliance with regulations like GDPR by ensuring that sensitive business and customer details are anonymized, securely stored, and only accessible to authorized parties. This work ensures organizational and stakeholder data privacy by using only anonymized data in compliance with regulations. Another concern is the risk of algorithmic bias, which can occur if AI systems are trained on incomplete or skewed datasets, potentially resulting in suboptimal recommendations. The HAI-HDM framework proactively addresses this by using explainable AI methods (such as SHAP and LIME) alongside human input to make recommendations more transparent and accountable.

CONCLUSION AND FUTURE WORK

This research introduces the Human-AI Hybrid Decision-Making framework as a strategic approach to address the complex challenge of technology adoption in SMEs. SMEs often encounter significant barriers when navigating digital transformation, stemming from limited resources, evolving business environments, and

the growing complexity of available technological options. The HAI-HDM framework is designed to alleviate these difficulties by integrating the predictive capabilities of artificial intelligence with the experiential knowledge and contextual understanding of human decision-makers.

Unlike conventional AI systems that may lack interpretability or overlook domain-specific nuances, and human-only approaches that are susceptible to bias and inconsistency, HAI-HDM employs a balanced human-in-the-loop model. This architecture incorporates explainable AI techniques, such as SHAP and LIME, to enhance the transparency and trustworthiness of system-generated recommendations. Simultaneously, it leverages machine learning and reinforcement learning algorithms to enable data-driven insights, dynamically adjusted through a weighted fusion mechanism that reflects both AI outputs and stakeholder preferences.

The system's iterative learning mechanism allows it to adapt continuously by incorporating feedback from real-world outcomes and human expertise, thereby improving its performance over time. Experiments using a simulated dataset of SME cloud service adoption scenarios indicate that the proposed framework produces promising results in identifying suitable technologies, improving stakeholder satisfaction, and demonstrating robustness, with comprehensive benchmarking left for future studies. By effectively combining analytical intelligence with human judgment, HAI-HDM represents an important step toward democratizing advanced decision support systems for SMEs. It promotes more inclusive, responsive, and transparent decision-making, well-suited to the dynamic nature of modern business. Future work will explore its application in domains such as healthcare and manufacturing, enhance its domain-specific reasoning capabilities through ontological modeling, and further refine its explainability features to build trust and usability in diverse organizational contexts.

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Author Contributions

- Chetna Gupta conceived and designed the experiments, performed the experiments, performed the computation work, authored or reviewed drafts of the article, and approved the final draft.
- Varun Gupta conceived and designed the experiments, performed the experiments, analyzed the data, performed the computation work, prepared figures and/or tables, and approved the final draft.

Data Availability

The following information was supplied regarding data availability:

The dataset is available in the [Supplemental Files](#).

Supplemental Information

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REFERENCES

- Ahmed SY, Pardaev J. 2025. Human-AI decision dynamics: how risk propensity and trust impact choices through decision fatigue, conditional on AI understanding. *Decision Making: Applications in Management and Engineering* 8(2):96–113.
- Al Khasawneh M, Abuhashesh M, Ahmad A, Masa'deh R, Alshurideh MT. 2021. Customers online engagement with social media influencers' content related to COVID 19. *Studies in Systems, Decision and Control* 334(10223):385–404 DOI 10.1007/978-3-030-67151-8_22.
- Awa HO, Ojiabo OU, Emecheta BC. 2015. Integrating TAM, TPB and TOE frameworks and expanding their characteristic constructs for e-commerce adoption by SMEs. *Journal of Science & Technology Policy Management* 6(1):76–94 DOI 10.1108/jstpm-04-2014-0012.
- Bettoni A, Matteri D, Montini E, Gladysz B, Carpanzano E. 2021. An AI adoption model for SMEs: a conceptual framework. *IFAC-PapersOnLine* 54(1):702–708 DOI 10.1016/j.ifacol.2021.08.082.
- Berruti F, Phal A, Rougeaux C. 2021. *Managing the risks and returns of intelligent automation*. New York: McKinsey & Company. Available at <https://www.mckinsey.com/capabilities/operations/our-insights/managing-the-risks-and-returns-of-intelligent-automation>.
- Bindeebe DS, Tukamushaba EK, Bakashaba R. 2025. Digital transformation and its multidimensional impact on sustainable business performance: evidence from a meta-analytic review. *Future Business Journal* 11(1):90 DOI 10.1186/s43093-025-00511-z.
- Bresciani S, Ferraris A, Romano M, Santoro G. 2021. Building a digital transformation strategy. In: *Digital Transformation Management for Agile Organizations: A Compass to Sail the Digital World*. Leeds: Emerald Publishing, 5–27.
- Carayannis EG, Dumitrescu R, Falkowski T, Papamichail G, Zota NR. 2025. Enhancing SME resilience through artificial intelligence and strategic foresight: a framework for sustainable competitiveness. *Technology in Society* 81(3):102835 DOI 10.1016/j.techsoc.2025.102835.
- Carayannis EG, Dumitrescu R, Falkowski T, Zota NR. 2024. Empowering SMES-harnessing the potential of gen AI for resilience and competitiveness. *IEEE Transactions on Engineering Management* 71:14754–14774 DOI 10.1109/TEM.2024.3456820.
- Dal Mas F, Massaro M, Ndou V, Raguseo E. 2023. Blockchain technologies for sustainability in the agrifood sector: a literature review of academic research and business perspectives. *Technological Forecasting and Social Change* 187(2):122155 DOI 10.1016/j.techfore.2022.122155.
- Ghasemaghaei M, Ebrahimi S, Hassanein K. 2018. Data analytics competency for improving firm decision-making performance. *The Journal of Strategic Information Systems* 27(1):101–113 DOI 10.1016/j.jsis.2017.10.001.
- Giachino C, Cepel M, Truant E, Bargoni A. 2024. Artificial intelligence-driven decision making and firm performance: a quantitative approach. *Management Decision* 10:1966 DOI 10.1108/MD-10-2023-1966.

- Grobrügge A, Mishra N, Jakubik J, Satzger G. 2024. Explainability in AI-based applications—a framework for comparing different techniques. In: *2024 26th International Conference on Business Informatics (CBI)*. Piscataway: IEEE, 70–79.
- Gupta C, Fernandez-Crehuet JM, Gupta V. 2022. Measuring impact of cloud computing and knowledge management in software development and innovation. *Systems* **10**(5):151 DOI [10.3390/systems10050151](https://doi.org/10.3390/systems10050151).
- Haenlein M, Kaplan A. 2019. A brief history of artificial intelligence: on the past, present, and future of artificial intelligence. *California Management Review* **61**(4):5–14 DOI [10.1177/0008125619864925](https://doi.org/10.1177/0008125619864925).
- Hasan MM. 2023. Understanding model predictions: a comparative analysis of SHAP and LIME on various ML algorithms. *Journal of Scientific and Technological Research* **5**(1):17–26 DOI [10.59738/jstr.v5i1.23\(17-26\).eaqr5800](https://doi.org/10.59738/jstr.v5i1.23(17-26).eaqr5800).
- Holl A, Rama R. 2024. Spatial patterns and drivers of SME digitalisation. *Journal of the Knowledge Economy* **15**(2):5625–5649 DOI [10.1007/s13132-023-01257-1](https://doi.org/10.1007/s13132-023-01257-1).
- Islam A, Bouzerdoum A, Belhaouari SB. 2024. Bio-inspired adaptive neurons for dynamic weighting in artificial neural networks. ArXiv DOI [10.48550/ArXiv.2412.01454](https://doi.org/10.48550/ArXiv.2412.01454).
- Liu L, Liu Y. 2025. AI-assisted decision-making and dynamic trust in lean construction: synergy mechanisms and insights. *Engineering, Construction and Architectural Management* **44**(3):1035 DOI [10.1108/ecam-01-2025-0093](https://doi.org/10.1108/ecam-01-2025-0093).
- Mahroof K. 2019. A human-centric perspective exploring the readiness towards smart warehousing: the case of a large retail distribution warehouse. *International Journal of Information Management* **45**(5):176–190 DOI [10.1016/j.ijinfomgt.2018.11.008](https://doi.org/10.1016/j.ijinfomgt.2018.11.008).
- Mensah JK, Xu Y. 2025. Adoption of E-commerce technologies among SMEs in Ghana under the influence of integrated UTAUT and TOE frameworks. *Information Development* **11**:1217 DOI [10.1177/026666669251325479](https://doi.org/10.1177/026666669251325479).
- Muminova E, Ashurov M, Akhunova S, Turgunov M. 2024. AI in small and medium enterprises: assessing the barriers, benefits, and socioeconomic impacts. In: *2024 International Conference on Knowledge Engineering and Communication Systems (ICKECS)*. Vol. 1, Piscataway: IEEE, 1–6 DOI [10.1109/ICKECS61492.2024.10616816](https://doi.org/10.1109/ICKECS61492.2024.10616816).
- OECD. 2021. Artificial intelligence: changing landscape for SMEs. Available at https://read.oecd-ilibrary.org/industry-and-services/the-digital-transformation-of-smes_01a4ae9d-en.
- Oseni A, Moustafa N, Janicke H, Liu P, Tari Z, Vasilakos A. 2021. Security and privacy for artificial intelligence: opportunities and challenges. ArXiv DOI [10.48550/ArXiv.2102.04661](https://doi.org/10.48550/ArXiv.2102.04661).
- Rialti R, Zollo L. 2023. Digital transformation of SME marketing strategies. Available at <https://doi.org/10.1007/978-3-031-33646-1>.
- Sotamaa T, Reiman A, Kauppila O. 2025. Manufacturing SME risk management in the era of digitalisation and artificial intelligence: a systematic literature review. *Continuity & Resilience Review* **7**(1):1–28 DOI [10.1108/CRR-12-2023-0022](https://doi.org/10.1108/CRR-12-2023-0022).
- Sudirman ID, Astuty E, Aryanto R. 2025. Enhancing digital technology adoption in SMEs through sustainable resilience strategy: examining the role of entrepreneurial orientation and competencies. *Journal of Small Business Strategy* **35**(1):97–114 DOI [10.53703/001c.124907](https://doi.org/10.53703/001c.124907).
- Tubastuvi N, Purwidiyanti W. 2023. Performance of women-led SMEs in Indonesia: the role of financial inclusion, financial literacy, and technology adoption. *Journal of Law and Sustainable Development* **11**(12):e1899 DOI [10.55908/sdgs.v11i12.1899](https://doi.org/10.55908/sdgs.v11i12.1899).
- Vimbi V, Shaffi N, Mahmud M. 2024. Interpreting artificial intelligence models: a systematic review on the application of LIME and SHAP in Alzheimer’s disease detection. *Brain Informatics* **11**(1):10 DOI [10.1186/s40708-024-00222-1](https://doi.org/10.1186/s40708-024-00222-1).

- Von Krogh G. 2018.** Artificial intelligence in organizations: new opportunities for phenomenonbased theorizing. *Academy of Management Discoveries* **4**(4):404–409 DOI [10.5465/amd.2018.0084](https://doi.org/10.5465/amd.2018.0084).
- Zamani SZ. 2023.** *Empowering small business: the impact of technology on US small business*. Washington, D.C.: US Chamber of Commerce Technology Engagement Center, 1–40.
- Zhang X, Zhang J, Si W, Liu K. 2024.** Dynamic weight adjusting deep Q-networks for real-time environmental adaptation. In: *2024 IEEE International Conference on Knowledge Graph (ICKG)*. Piscataway: IEEE, 500–507 DOI [10.1109/ICKG63256.2024.00070](https://doi.org/10.1109/ICKG63256.2024.00070).