Journal of Computers, Mechanical and Management
Journal homepage: www.jcmm.co.in
e-ISSN: 3009-075X

Volume 4 Issue 6
Article Number: 25232

Predictive Analytics Model for AI-Enhanced Decision Support in Corporate Management

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Abstract

AI and predictive analytics have revolutionized corporate management by replacing guesswork with facts. A comprehensive literature review reveals that AI-enhanced decision support systems are increasingly incorporating machine learning predictive analytics models. This paper summarizes research from academic studies and case studies performed by businesses to demonstrate how predictive analytics becomes an integrated part of planning corporate strategy, allocating resources among departments, and ensuring administrative efficiency. This study focuses on classifiers, which are fundamental machine learning techniques for predicting and simplifying complex decision-making processes. Such techniques include neural networks, regression analysis, decision trees, and others. The authors explain the various aspects to consider when implementing AI-driven solutions successfully, including data quality, model interpretability, and ethics. The findings show that organizations adopting predictive analytics report measurable improvements, including up to 15% reduction in employee turnover, 20–30% improvement in risk mitigation, 25% sales growth, and 40% reduction in operational inefficiencies when integrated with ERP systems. The study also examines how predictive analytics is affecting various disciplines, such as risk management, market trend forecasting, and employee performance appraisal, by analyzing specific real-life examples. Findings suggest that the implementation of real-time analytics in ERP systems has the potential to enhance strategic decision-making significantly. The review also reveals gaps in the literature and contributes to future research by highlighting the need to scale solutions to problems and applications across industries.

Keywords: Predictive Analytics; Decision Support Systems; Artificial Intelligence; Corporate Management

1. Introduction

As artificial intelligence (AI) and predictive analytics are integrated in corporate management, the management of a corporation is experiencing a major revolution that will enable organizations to make informed decisions. With business environments becoming increasingly dynamic, organizations are turning to AI-based models to enhance efficiency, optimize resource utilization, and develop strategic plans [1]. Traditional decision-making methods, which rely primarily on intuition and past experiences, are hardly adequate in the modern, high-speed, competitive marketplace [2]. AI-powered decision support systems bridge this gap by providing correct predictions, scenario analysis, and automatic suggestions.

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Received: 3 Nov 2025; **Revised:** 10 Dec 2025; **Accepted:** 13 Dec 2025; **Published:** 31 Dec 2025

DOI: 10.57159/jcmm.4.6.25232.

Additionally, these systems are quite useful in risk management, financial forecasting, analyzing financial market trends, and planning human resource activities in organizations. Predictive analytics enables businesses to anticipate threats and opportunities better.

The proposed research aims to conduct a systematic review of the literature to explore predictive analytics models of AI-mediated decision support in corporate management. The current review outlines the relevant machine learning methodologies in predictive analytics, the potential of machine learning to either advantage or disadvantage decision-making, and the effects of machine learning on administrative efficiency, strategic planning, and resource management. Additionally, this study examines issues and problems related to AI-based decision support, including data quality, model interpretability, and ethical considerations. The study aims to gain an understanding of what has already been accomplished, while also identifying what needs to be understood in the future through a synthesis of scholarly articles and industry case studies [3]. The following systematic research questions guide this review:

RQ1: What predictive analytics models are most commonly applied in AI-driven decision support systems for corporate management?

RQ2: How do predictive analytics techniques (e.g., regression, neural networks, decision trees) improve decision-making in areas such as resource allocation, risk management, and performance evaluation?

RQ3: What challenges (e.g., data quality, interpretability, ethics) limit the effective adoption of AI-enhanced predictive analytics in corporate decision making?

RQ4: What gaps exist in the current literature, and how can predictive analytics models be adapted for scalability and cross-industry application?

This review adds value to the existing literature in three respects. First, it combines empirical evidence from HR, finance, operations, marketing, and ERP functions, showing that similar patterns of where predictive analytics offers the most value emerge. Second, it presents a comparative analysis of popular predictive models, with trade-offs in accuracy, interpretability, and scalability commonly reported in previous reviews. Third, it reveals industry differences by demonstrating how studies are concentrated in finance and retail, while limited research is available in public administration, education, and agriculture. These insights provide both theoretical and practical guidance on designing future AI-assisted decision systems.

A systematic literature review approach has been employed to analyze the available studies systematically. This includes conceptualization, in which pertinent academic and industry literature is identified and selected, inclusion and exclusion criteria are defined, and results are synthesized through thematic analysis. The peer-reviewed journal articles, conference papers, and case studies included in this review address the integration of AI and predictive analytics in corporate decision making [4]. This study integrates findings from various sources to demonstrate how predictive analytics can be developed to support an evolving corporate management environment.

2. Literature Review

The use of AI-powered decision-making software to sift through large data volumes and identify actionable insights should be part of every business management process. Enterprises can mitigate risks by leveraging AI and machine learning to predict market trends and enhance efficiency. The conventional decision-making paradigm is based on human experience or past experiences. Conversely, AI-based systems utilize computational capabilities to process historical and real-time data in parallel. The competitive environment and the need to address key market perturbations make AI-based decision support systems (DSS) relied upon across a wide variety of industries [5].

Predictive analytics provides models that recognize trends and generate forecasts through data-driven analysis. Decision trees, regression analysis, and neural networks are among the most widely used machine learning models in business decision-making [6]. Regression is a statistical method for establishing relationships between variables and is widely used in finance, sales, and risk management. Regression models enable managers to identify the effects of various factors on organizational outcomes and justify decision-making through empirical data.

Another important process in predictive analytics is neural networks (NNs), which are designed based on the operations of the human brain. They consist of deep layer-based architectures composed of artificial neurons that process information and detect complex patterns. Neural networks are suitable for large-scale data problems and possess the capability to model nonlinear relationships among variables. These characteristics make them appropriate for demand prediction, fraud detection, and consumer behavior analysis. Deep learning, a subclass of neural networks, has also been utilized in predictive analytics to enhance model accuracy and feature learning [7]. Decision trees represent another widely used machine learning model that is simple and interpretable for decision-making. These models divide data into multiple hierarchically structured branches based on specific attributes to reach conclusions.

Commercial applications of decision trees include strategic planning, staff performance evaluation, and credit risk assessment, among others [8]. Managers without technical expertise can understand decision trees due to their logical and transparent representation of the decision-making process.

Predictive analytics is applied extensively in corporate management for strategic planning, resource allocation, and administrative efficiency. Automation and optimization of routine business processes enable organizations to streamline workflows, optimize customer service processes, and forecast demand by predicting workloads [9]. Conversational bots powered by machine learning can enhance response speed and user satisfaction by effectively addressing customer requests. In industrial sectors, predictive maintenance systems improve efficiency and reduce costs by using sensor data to prevent equipment failures.

Resource allocation represents another critical area where predictive analytics provides value. To maximize productivity and profitability, organizations must effectively manage resources, including labor, capital, and inventory. AI-based models facilitate demand forecasting, enabling firms to manage inventory based on projected sales [10]. In healthcare, predictive analytics supports staff scheduling, patient flow estimation, and resource utilization monitoring. Optimizing logistics and supply chains using AI can also reduce transportation costs by enhancing inventory placement and routing decisions. From a strategic perspective, predictive analytics enables organizations to understand market trends and competitive forces by analyzing consumer behavior, economic indicators, and industry developments.

Predictive analytics provides decision-makers with insights into emerging opportunities and risks, thereby enhancing long-term organizational planning [11]. Financial institutions employ machine learning algorithms for tasks such as investment risk assessment and portfolio predictive modeling [12].

Despite the benefits of AI-driven decision support systems, challenges remain, particularly regarding data quality. Biased, incomplete, inconsistent, or otherwise flawed datasets can result in inaccurate predictions and poor decision-making [13]. Consequently, data cleaning, validation, and monitoring processes are critical for ensuring reliable predictive outcomes. Ethical concerns related to model use and decision automation must also be addressed. By overcoming these challenges, organizations can fully leverage predictive analytics to enhance innovation, operational efficiency, and competitive advantage in dynamic business environments.

Although regression, neural networks, and decision trees are widely adopted, the reviewed studies reveal notable trade-offs among these models. Regression models are favored in finance and HR analytics due to their interpretability and moderate computational cost, but are limited in capturing complex nonlinear relationships. Neural networks and deep learning architectures achieve higher predictive accuracy in large-scale marketing and demand forecasting tasks, but require extensive data, specialized expertise, and lack interpretability due to their black-box nature. Decision trees and ensemble methods, such as random forests, offer a balance between accuracy and interpretability; however, they may suffer from overfitting and increased complexity when grown to a deep level. These findings suggest that corporate decision support model selection should balance accuracy, scalability, and interpretability rather than prioritizing a single performance criterion.

3. Methodology

A systematic literature review approach is employed to ensure a comprehensive analysis of the existing literature on AI-based approaches to predictive analytics for corporate decision support. Papers were selected according to specific inclusion and exclusion criteria to filter insights on machine learning techniques and decision support systems for corporations. Peer-reviewed journal articles, conference papers, and industry case studies highlighting the integration of predictive analytics and AI in business settings were collected. To ensure quality, preference was given to papers published in credible journals and conferences, ensuring the applicability of the findings to modern corporate management practices. Purely theoretical papers without empirical analysis were excluded.

A literature search was conducted on academic databases with strong coverage of research on AI, business analytics, and corporate management. To structure the review systematically, the PICOC (Population, Intervention, Comparison, Outcome, Context) framework was applied, as presented in Table 1.

The databases included Scopus, Web of Science, IEEE Xplore, ScienceDirect, and Google Scholar. Industry reports and white papers were also reviewed to obtain insights into real-world applications and emerging trends in predictive analytics. Using multiple IT-focused databases ensured a broad and diverse range of papers and reduced the risk of bias. Table 2 summarizes the online database search process.

Explicit inclusion and exclusion criteria were employed to ensure transparency and reproducibility. Studies were included if they (i) adopted AI-enhanced predictive analytics models (regression, neural networks, or decision trees), (ii) analyzed applications in corporate or organizational decision-making, and (iii) reported empirical evidence, case studies, or measurable performance metrics.

Table 1: PICOC Framework

Element	Description
Population	Corporations and organizations across industries (finance, retail, HR, manufacturing, etc.)
Intervention	AI-enhanced predictive analytics (regression, neural networks, decision trees, automation)
Comparison	Traditional decision support systems based on intuition/manual analysis
Outcome	Improved decision quality, reduced risks, efficiency gains, better resource allocation
Context	Corporate decision-making processes (strategic planning, risk management, HR, ERP systems)

Table 2: Online Database Search (Phase 1 & Phase 2)

Database	Search Results	Phase 1 (Screened)	Phase 2 (Included)
Scopus	520	140	50
Web of Science	410	120	40
IEEE Xplore	330	100	35
ScienceDirect	460	135	42
Google Scholar	600	160	53

Studies were excluded if they were purely theoretical, lacked methodological detail, focused solely on algorithm development without managerial implications, or were not written in English. Reference management software was used to remove duplicate records. Screening was conducted in two phases: title and abstract screening, followed by full-text assessment based on methodological transparency, model reporting, and relevance to the research questions.

A systematic search strategy, utilizing combinations of keywords, was employed to retrieve relevant studies. Core keywords included predictive analytics, AI-driven decision support, machine learning in business, corporate decision-making, data-driven management, and business intelligence systems. Boolean operators were used to refine searches, such as "predictive analytics AND corporate management" and "AI AND decision support systems." Filters were applied to include peer-reviewed journal articles, conference proceedings, and research papers published between 2014 and 2024. Studies offering transferable insights for corporate decision-making across sectors were included, including industry-specific applications such as healthcare and finance.

The selected studies were evaluated using quality indicators, including research methodology, sample size, data sources, and the robustness of the conclusions. Preference was given to empirical studies, case studies, and experimentally validated research. Methodological rigor in the development of machine learning models for predictive analytics was considered, including data pre-processing techniques, evaluation metrics, and comparative analysis with traditional decision-making approaches. Studies lacking methodological transparency or sufficient reporting of predictive model performance were excluded.

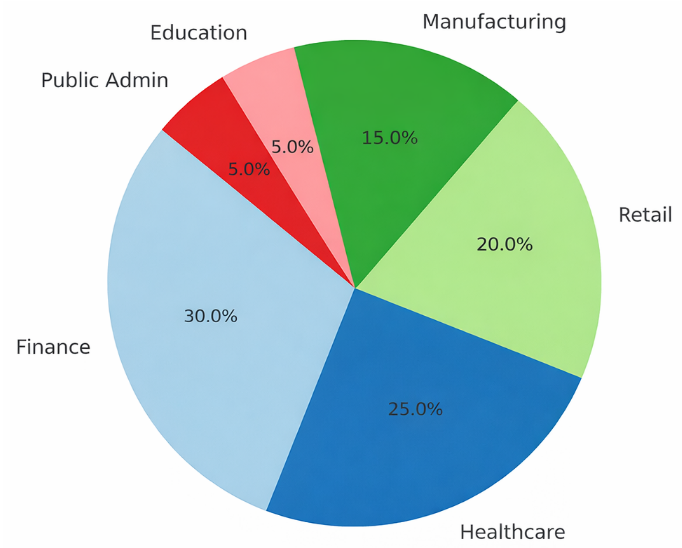

Figure 1: Distribution of Research by Industry Sector (2014–2024)

As illustrated in Figure 1, the finance sector exhibits the highest concentration of studies, reflecting its early adoption of data-driven decision support and access to large, structured datasets suitable for predictive modeling. Retail and manufacturing follow due to their reliance on demand forecasting and operational optimization. In contrast, education and public administration remain underrepresented, primarily due to fragmented data systems, regulatory constraints, and slower digitalization. This imbalance affects the generalizability of findings, as results from finance and retail may not be directly transferable to underrepresented sectors without significant adaptation of models and data governance frameworks. Based on a systematic review and analysis of the literature, this study aims to provide a comprehensive, evidence-based perspective on the role of AI-based predictive analytics in corporate management. The methodology enables the identification of key trends, challenges, and research gaps while ensuring that conclusions are drawn from high-quality sources. Through the systematic literature review methodology, rigor, replicability, and completeness are achieved by applying transparent search, screening, and selection procedures. Studies lacking empirical evidence or methodological clarity were excluded. The thematic synthesis of the final set of articles reveals common machine learning methods, industry applications, and adoption challenges, thereby reducing bias and strengthening the validity of the findings.

4. Results and Discussion

The systematic literature review indicates a growing role for predictive analytics in AI-based decision support systems used in business management. Numerous case studies demonstrate how predictive analytics models contribute to business in fundamental areas, including employee performance evaluation, risk assessment, and market trend forecasting. These applications demonstrate the importance of AI in enhancing the decision-making process, resource allocation, and overall organizational effectiveness. Employee performance appraisal case studies suggest the potential for tracking metrics using predictive analytics, providing organizations with a credible view of employee productivity. AI systems can analyze historical performance data, attendance records, and employee engagement data to identify trends that indicate whether future performance is likely to be high or low. Organizations have forecast employee attrition using machine learning algorithms such as regression analysis and neural networks and taken preemptive measures to retain talent. One study reports that workplace turnover rates dropped by 15% in organizations that implemented AI-based performance appraisal systems, as these systems enable more targeted workforce retention policies. Additionally, predictive models enable managers to focus training activities more effectively, ensuring that employees receive individualized development plans tailored to specific skill development pathways.

Risk management is another domain where predictive analytics transforms corporate decision-making. Organizations are vulnerable to various risks, including financial losses, cyberattacks, and logistical disruptions. Decision trees and deep learning models can interpret real-time data to anticipate potential risks before they occur. For example, predictive analytics enables financial institutions to detect fraudulent transactions through behavioral profiling. Manufacturing firms utilize artificial intelligence to predict equipment failures and implement proactive maintenance, leading to a significant reduction in operational disruptions. Case studies indicate that organizations using AI-based risk assessment systems have achieved 20–30% improvements in risk mitigation efficiency, leading to cost reductions and improved business continuity. In the financial sector, predictive analytics is applied by hedge funds and investment firms to support portfolio management and investment decision-making [12]. Organizations make data-driven strategic decisions by leveraging machine learning models to analyze consumer behavior, economic indicators, and industry trends, thereby informing informed decisions. For instance, retail corporations utilize AI algorithms to forecast product demand, automate inventory management, and tailor marketing activities. Studies of e-commerce companies indicate that many organizations adopting AI-based market forecasting achieved approximately a 25% increase in sales due to improved demand prediction and targeted advertising strategies. In the financial sector, predictive analytics is applied by hedge funds and investment firms to support portfolio management and investment decision-making.

Predictive analytics further enhances corporate decision-making capabilities when integrated with enterprise resource planning (ERP) systems. ERP platforms manage core business processes, including finance, human resources, supply chain, and customer relationship management. Integrating predictive analytics into ERP systems enables organizations to analyze real-time data, optimizing operational efficiency and informing strategic planning. Case studies report up to a 40% reduction in inefficiencies when AI-driven predictive models are embedded in ERP workflows. These efficiency gains are often attributed to models such as gradient-boosted trees, random forests, and deep learning networks that automate anomaly detection, production scheduling, and inventory optimization. However, the magnitude of improvement varies across industries. Sectors with rich, structured, and high-frequency data, such as logistics and manufacturing, experience greater benefits, while HR and strategic planning functions show more modest improvements due to reliance on qualitative or unstructured data. By analyzing historical interactions and anticipating future needs, predictive analytics enables organizations to forecast market demand, optimize production schedules, and enhance customer service.

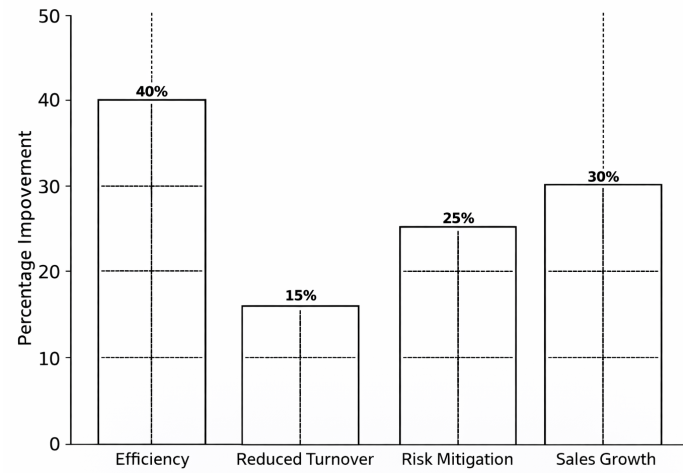

Figure 2: Benefits of AI-Driven Predictive Analytics in Corporate Decision-Making

As Figure 3 illustrates, efficiency and risk reduction prevail over the reported benefits, meaning that current AI usage is centered on operational and cost-centre benefits. Strategic advantages such as innovation and long-term planning are less common, indicating that AI-powered predictive analytics are more frequently utilized for process optimization rather than strategic transformation. Notwithstanding these advantages, several structural issues continue to restrain the use of AI. Data quality problems may include missing values, biased historical records, and unreconciled data sources, which can compromise predictions and lead to overconfidence in inaccurate results. The literature reports limited use of explainable AI (XAI) methods, such as SHAP, LIME, or surrogate models, which generate transparency gaps that reduce managerial trust [14]. Ethical issues are also frequently highlighted, including algorithmic bias, privacy risks, and the lack of clear accountability when automated predictions are used in high-stakes business decisions [15]. Without effective data governance and explainability mechanisms, organizations risk implementing models that may be statistically accurate but misaligned with ethical and managerial requirements. While AI-enabled decision support methodologies and technologies have advanced significantly, several research gaps remain, particularly in terms of scalability and cross-industry applicability. Data requirements for storing and processing predictive outcomes can be substantial, especially for complex models, limiting adoption by organizations with rudimentary IT capabilities. Although predictive analytics has been widely applied in finance, healthcare, and retail sectors, empirical literature in areas such as agriculture, construction, education, and public administration remains limited or is still in its early stages. Broader cross-industry research is necessary to determine how predictive analytics can be adapted to diverse business contexts. The literature also indicates limited attention to successful applications of AI across multiple industries without the heavy engineering typically required for advanced methods (up to October 2020). Improving machine learning interpretability is critical for building trust and encouraging adoption among corporate decision-makers. Furthermore, issues related to model bias and data privacy warrant further investigation when considering the ethical implications of AI-driven decision support.

Table 3: Key Findings from Case Studies

Business Application	AI Techniques Used	Observed Benefits
Employee Performance Evaluation	Regression, Neural Networks	Reduced turnover by 15%, improved workforce productivity
Risk Management	Decision Trees, Deep Learning	20–30% improvement in risk mitigation efficiency
Market Trend Forecasting	Machine Learning, AI-driven Analytics	25% increase in sales, optimized marketing strategies
ERP System Integration	Predictive Analytics, Automation	40% reduction in inefficiencies, enhanced decision-making

When examined across different business functions, distinct cross-industry trends emerge. HR applications show modest but strategically significant improvements, such as a 15% reduction in employee turnover associated with targeted retention strategies. Risk management delivers greater efficiency gains of 20–30%, as timely anomaly detection directly reduces losses and downtime. Market forecasting yields revenue growth of approximately 25% through integration with personalized marketing and dynamic pricing. The greatest operational impact, reflected in a 40% efficiency gain, is observed with ERP integration, where multiple processes are optimized simultaneously.

These patterns demonstrate that the effectiveness of predictive analytics depends on the extent to which model outputs are embedded within organizational operations. All numerical improvements reported in this section were extracted directly from empirical case studies included in the final SLR dataset. Several limitations should be acknowledged in interpreting the findings of this systematic review. First, the literature search was limited to English-language publications, which may have excluded relevant studies published in other languages. Second, despite using multiple reputable academic databases, publication bias may be present, as studies reporting negative or inconclusive results are less likely to be published. Third, the selected review period (2014–2024) may have excluded earlier foundational studies relevant to predictive analytics and decision support systems. Fourth, variations in evaluation metrics across the reviewed studies limited the ability to conduct direct quantitative comparisons. Finally, empirical evidence remains scarce in sectors such as agriculture, education, and public administration, which restricts the generalizability of the findings across all industries. These limitations should be considered when interpreting the results and guiding future research.

5. Conclusions

This study presents a systematic literature review of AI-enhanced predictive analytics models in corporate decision support, demonstrating the potential of machine learning as a disruptive technology that influences how organizations operate in modern environments. The findings indicate that predictive analytics contributes to decision-making across multiple corporate functions, including employee performance evaluation, risk management, market forecasting, and resource planning, by providing data-driven insights. AI-driven models enable more accurate task execution, saving valuable time and reducing costs, while enhancing administrative efficiency, improving resource utilization, and streamlining planning processes. The case studies reviewed reveal tangible benefits, including reduced employee turnover, improved risk mitigation, increased sales through market prediction, and enhanced operational efficiency through ERP system integration. The impact on corporate decision-making is significant, as predictive analytics enables organizations to move from reactive strategies toward preventive actions. Firms implementing AI-driven decision support systems can generate accurate forecasts of market trends, manage workforce dynamics, and anticipate risks before they escalate. The ability to process large volumes of data uncovers hidden patterns that support faster and more confident managerial decision-making. Predictive analytics has also facilitated the automation of business processes, leading to reduced inefficiencies and lower operational costs. However, to fully realize these benefits, organizations must establish robust data architectures, ensure model transparency, and address ethical concerns, including bias and data privacy protection. A key insight from the review is that the scalability of predictive analytics varies across different industries. Sectors such as finance and retail benefit from structured, high-volume transactional data that supports rapid deployment of high-performance models. In contrast, industries such as agriculture, public administration, and education often rely on sparse or fragmented datasets, limiting the applicability of complex algorithms. These sectors may require lightweight, interpretable, and data-efficient models rather than high-capacity architectures. Addressing these differences should be a focus of future research, with an emphasis on cross-industry adaptation strategies rather than the direct transfer of data-intensive models. Overall, predictive analytics models have the capacity to enhance corporate decision support by providing data-driven insights that improve efficiency, risk management, and strategic planning. While the benefits of AI-based decision-making are evident, challenges related to scalability, interpretability, and ethical considerations must be addressed to maximize impact. Progress in these areas will support the continued refinement of AI-based predictive analytics frameworks to meet evolving corporate management needs, promoting sustainable business growth and innovation. This review directly addresses the four research questions by identifying commonly used predictive models in corporate settings (RQ1), explaining how these models enhance decision quality across business functions (RQ2), synthesizing key adoption challenges related to data quality, ethics, and interpretability (RQ3), and highlighting cross-industry gaps that limit scalability (RQ4).

Declaration of Competing Interests

The authors declare no known competing financial interests or personal relationships.

Funding Declaration

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

Data Availability

All data supporting the findings of this study are included within the article.

AI Disclosure

The authors used an AI-based language tool to improve grammar and readability. The scientific content and conclusions were reviewed and validated by the authors.

Author Contributions

Zhang JianGang: Conceptualisation, Formal analysis, Investigation, Supervision, Writing – review and editing; **Hazirah Bee Yusof Ali**: Methodology, Data curation, Validation, Writing – original draft, Visualisation, Project administration.

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