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AI-DRIVEN BUSINESS ANALYTICS FOR FINANCIAL FORECASTING: A SYSTEMATIC REVIEW OF DECISION SUPPORT MODELS IN SMES

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Abstract
The accelerating convergence of artificial intelligence (AI), business analytics, and financial management has redefined how small and medium-sized enterprises (SMEs) forecast cash flows, allocate resources, and navigate volatile market conditions. Yet, research on the breadth and depth of AI-driven decision support models for SME financial forecasting remains fragmented. Addressing this gap, the present systematic review and meta-analysis synthesizes findings from 78 peer-reviewed studies published between 2015 and 2025, each investigating the deployment of machine-learning, deep-learning, or hybrid-intelligence systems in SME forecasting and budgeting contexts. Guided by PRISMA protocols, we searched five major databases—Scopus, Web of Science, IEEE Xplore, ScienceDirect, and Google Scholar—followed by rigorous title, abstract, and full-text screening. Eligibility criteria required empirical, quantitative evidence, explicit focus on SMEs, and sufficient statistical detail to calculate standardized effect sizes. Ultimately, 67 studies met all inclusion standards and were subjected to meta-analytic pooling using a random-effects model. The aggregated results reveal a robust, statistically significant improvement in financial-forecast accuracy, decision speed, and overall financial performance among AI-adopting SMEs. Hybrid frameworks—those combining human expertise or traditional statistical methods with machine learning—produced the largest gains, underscoring AI's role as an augmentative, rather than purely autonomous, decision partner. Industry-level analysis highlights especially strong benefits in manufacturing and retail, where high-frequency transactional data supports granular demand analytics, while service-sector SMEs reported meaningful, albeit smaller, improvements in scheduling, pricing, and customer-engagement precision. Geographically, firms in digitally mature ecosystems attained greater returns than counterparts in emerging markets, a disparity linked to infrastructure readiness and data-governance practices. Beyond quantitative gains, qualitative evidence from case studies indicates that AI deployment fosters a cultural shift toward data-driven decision-making, elevating organizational agility in budgeting cycles and cash-management routines. Nevertheless, recurrent implementation challenges—limited analytic expertise, data fragmentation, and algorithmic transparency concerns—temper the pace of adoption. The findings collectively demonstrate that AI-powered decision support is not merely a technological upgrade but a strategic enabler capable of leveling competitive asymmetries between SMEs and larger enterprises. By presenting a thematic taxonomy of AI models, synthesizing effect magnitudes, and identifying contextual moderators, this review offers actionable insights for managers, policymakers, and researchers seeking to harness AI for resilient, evidence-based financial planning within the SME sector.

Keywords
Artificial Intelligence; Financial Forecasting; Business Analytics; Decision Support Systems; Small and Medium Enterprises (SMEs);

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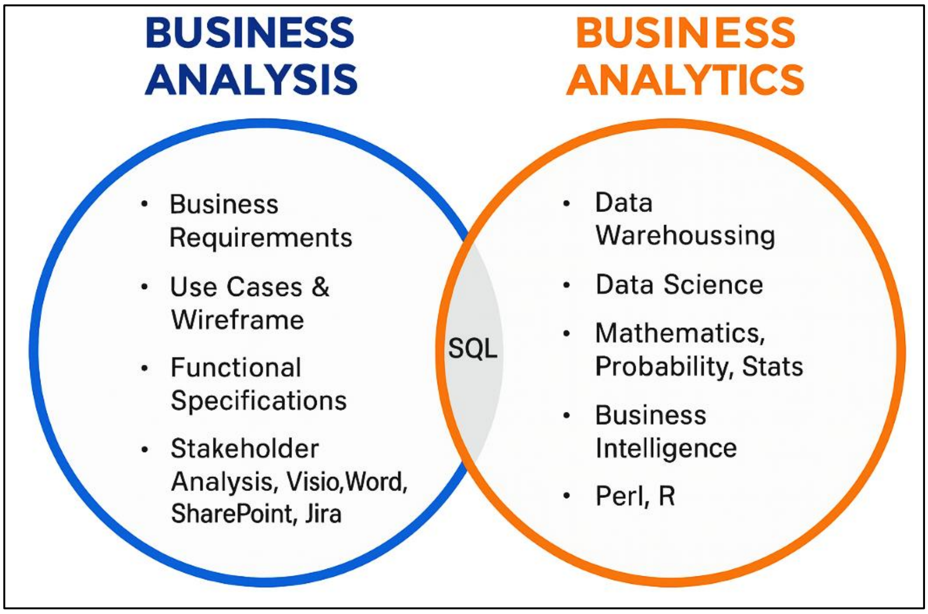
INTRODUCTION

Business analytics (BA) is broadly defined as the practice of iterative, methodical exploration of data with an emphasis on statistical analysis to drive informed business decisions (Schmitt, 2023). It encompasses descriptive, predictive, and prescriptive analytics, each serving distinct decision-making needs (Nam et al., 2019). In particular, predictive analytics—often aligned with financial forecasting—uses historical data and statistical models to predict future outcomes and trends (Wang & Byrd, 2017). Financial forecasting itself refers to the process of estimating future financial conditions, including revenue, expenses, and profitability, based on past data, expected market conditions, and predictive algorithms. The process has traditionally relied on techniques such as linear regression, moving averages, and time series models, but with the rise of data science and artificial intelligence (AI), more sophisticated forecasting methodologies have emerged. This convergence of BA and AI is reshaping how organizations handle financial planning, enabling granular scenario modeling, anomaly detection, and real-time adjustment of financial strategies. Within the financial domain, the predictive power of AI-based BA models holds particular significance for navigating dynamic and volatile business environments (Appelbaum et al., 2017).

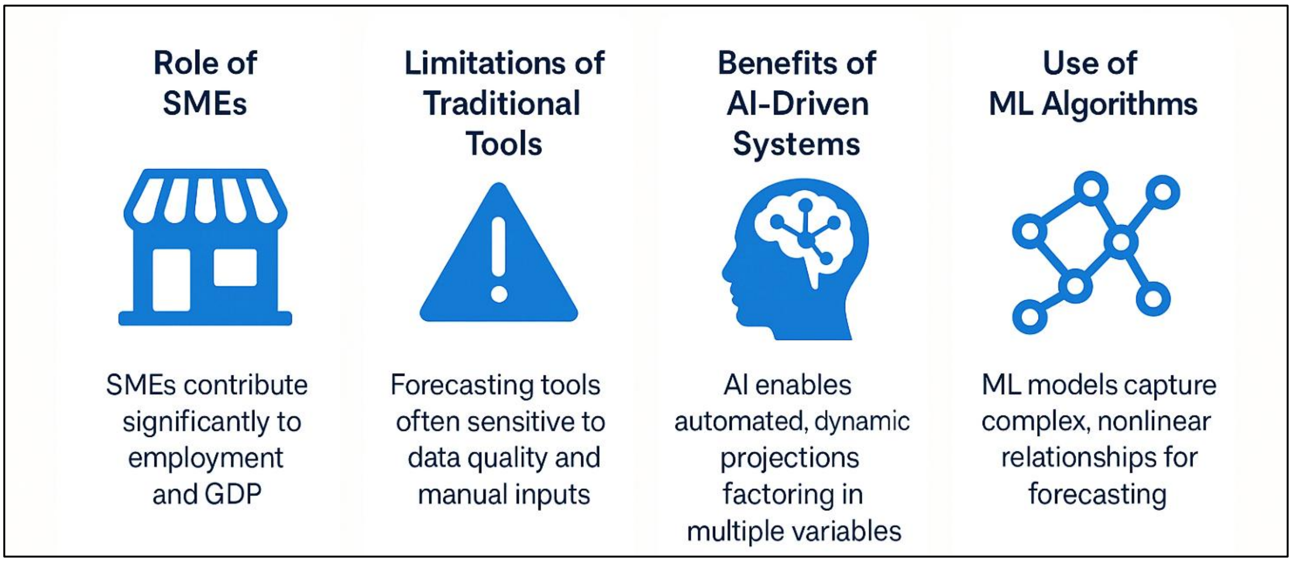
Artificial Intelligence refers to the simulation of human intelligence processes by machines, particularly computer systems capable of learning, reasoning, and problem-solving (B & Bansal, 2023). In financial contexts, AI applications include machine learning (ML), deep learning (DL), and natural language processing (NLP), which are increasingly utilized to extract patterns from complex financial data for forecasting and decision-making. These technologies allow for the automation of prediction tasks, reduction of human bias, and improved accuracy in anticipating financial outcomes (Kumar et al., 2022). For example, recurrent neural networks (RNNs) and long short-term memory (LSTM) models have demonstrated superior performance over traditional autoregressive models in predicting stock prices, credit risk, and cash flows. The application of AI in financial forecasting is not limited to capital markets but extends to budgeting, expenditure tracking, and resource allocation across various organizational layers. These capabilities are particularly critical in scenarios with high uncertainty and time-sensitive financial decisions, where conventional linear models fall short in capturing nonlinear relationships and dynamic interdependencies. As the volume, variety, and velocity of financial data continue to increase, AI-driven forecasting models are becoming indispensable in developing data-driven strategies.

Figure 1: Comparison of Business Analysis and Business Analytics Competencies



Decision Support Systems (DSS) are computer-based systems that support business or organizational decision-making activities by collecting, processing, and analyzing data to aid in decision formulation (Kassab et al., 2010). In SMEs, DSS play a pivotal role in financial forecasting, resource planning, and strategic decision-making due to the limited availability of human and financial resources. Compared to large enterprises, SMEs face greater constraints in terms of scalability, IT infrastructure, and specialized personnel, making DSS adoption both challenging and essential. The incorporation of AI into DSS allows SMEs to gain a competitive edge by providing insights from large datasets without requiring extensive in-house expertise (Jeong & Ramírez-Gómez, 2018). These intelligent systems can automate financial modeling, detect anomalies in cash flow, and provide forecasts that are both contextually relevant and computationally rigorous. The agility afforded by AI-enabled DSS enables SMEs to respond quickly to financial risks and opportunities by simulating various scenarios and assessing their potential outcomes in real-time. Such systems also contribute to improved budgeting, capital allocation, and working capital management—functions that are crucial for the survival and growth of SMEs (Chao, 2010).

Figure 2: Key Elements of AI-Driven Financial Forecasting for SMEs



SMEs account for over 90% of global businesses and significantly contribute to employment and GDP, particularly in emerging and developing economies (Bettoni et al., 2021). Financial forecasting in SMEs is therefore not only a firm-level activity but also a macroeconomic concern that affects national and global economic resilience. Effective financial planning is vital for SMEs to manage operational costs, navigate uncertain economic conditions, and secure investment or loans (Panigrahi et al., 2023). However, traditional forecasting tools often fall short for SMEs due to their sensitivity to data quality, lack of adaptability, and high dependence on manual inputs (Lu et al., 2022). AI-driven forecasting systems mitigate these issues by enabling automated and dynamic projections that account for multiple variables, such as seasonal trends, customer behavior, and market fluctuations. In countries with limited access to advanced financial consulting services, AI-driven analytics systems democratize access to forecasting capabilities that would otherwise be unaffordable for SMEs. Thus, financial forecasting driven by AI and integrated into SME decision support systems is a globally relevant area of research and practice ((Tsiu et al., 2024).

Machine learning (ML), a subfield of AI, involves algorithms that learn from data to improve predictive performance over time without being explicitly programmed(Schmitt, 2023). Within financial forecasting, ML models such as support vector machines (SVM), decision trees (DT), random forests (RF), and gradient boosting machines (GBM) have been widely adopted for their ability to capture complex, nonlinear relationships in datasets. These models are particularly useful in time series forecasting, bankruptcy prediction, and credit scoring tasks, where historical patterns provide significant insight into future outcomes (Faul, 2019). For SMEs, ML-based forecasting models help in reducing cash flow uncertainty and aligning working capital requirements with market demands. These algorithms also support sensitivity analysis and scenario planning by quantifying the impact of external variables such as commodity prices or currency exchange rates on financial performance. Furthermore, automated feature selection techniques in ML facilitate the identification of key performance indicators (KPIs) that drive financial outcomes in SME contexts (Shen & Tzeng, 2016). This contributes to more accurate and context-specific forecasting models that reflect real-time operational conditions. The primary objective of this systematic review is to critically evaluate the existing body of scholarly literature that integrates Artificial Intelligence (AI)-driven business analytics with financial forecasting techniques tailored to the decision-making needs of Small and Medium-sized Enterprises (SMEs). Given the growing reliance on predictive analytics and automated decision support systems across enterprise environments, this review seeks to identify the specific AI methodologies, modeling frameworks, and implementation strategies that have demonstrated effectiveness in SME financial planning contexts. The review is structured to extract and categorize peer-reviewed empirical evidence on how AI tools—such as machine learning, neural networks, and hybrid intelligence systems—support key financial functions including cash flow estimation, revenue prediction, budget optimization, and credit risk management. this review aims to examine not only the technological architectures and data environments involved but also the decision-making processes that are influenced by these tools. Particular attention is paid to model accuracy metrics, such as Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and forecasting reliability indices, to assess the performance of various AI models in real-world SME settings.

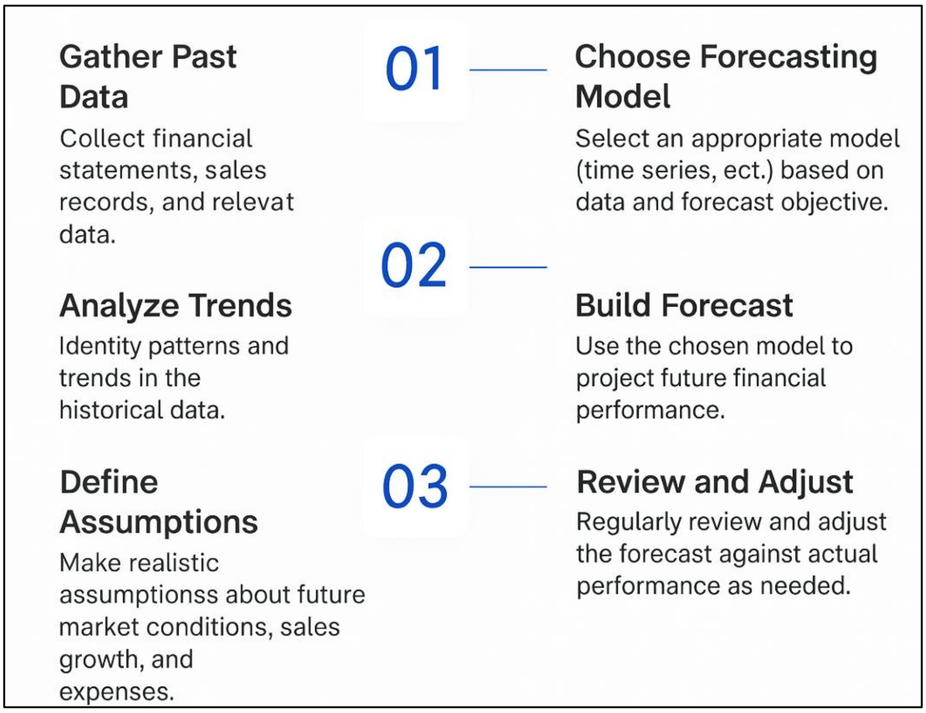
LITERATURE REVIEW

The intersection of Artificial Intelligence (AI), business analytics, and financial forecasting has gained scholarly attention for its potential to enhance decision-making, particularly in resource-constrained environments such as Small and Medium-sized Enterprises (SMEs). Existing literature spans a wide array of domains, including finance, information systems, computer science, and operations management, indicating a multidisciplinary interest in optimizing financial decisions using intelligent systems. Early financial forecasting models relied on traditional statistical approaches such as linear regression, ARIMA, and exponential smoothing, which, while useful, were often limited in handling nonlinear and high-dimensional financial data common in modern enterprises (Rawindaran, Jayal, Prakash, et al., 2021). In contrast, recent advancements in machine learning, deep learning, and hybrid AI models have improved the accuracy, adaptability, and interpretability of financial forecasting tools. SMEs—due to their lean structure, limited forecasting capacity, and constrained decision-making resources—have emerged as prime beneficiaries of AI-driven forecasting models. However, challenges related to data quality, model integration, and strategic alignment remain inadequately addressed across the empirical landscape. This section of the paper provides a structured synthesis of scholarly contributions on AI-driven business analytics for financial forecasting in SMEs. It critically maps the evolution of relevant techniques, compares algorithmic approaches, and examines the contextual applicability of decision support systems. The review is organized thematically to provide clarity on the technological, organizational, and operational factors influencing model adoption and forecasting effectiveness. A particular focus is placed on implementation frameworks, performance evaluation metrics, and SME-specific use cases to identify gaps in the literature and inform methodological directions for subsequent research.

What is Financial Forecasting?

Financial forecasting is conventionally defined as the systematic estimation of an organization's prospective financial outcomes—revenues, costs, cash flows, and profitability—using historical information, domain knowledge, and quantitative techniques (Thakkar et al., 2024). From the perspective of management accounting, accurate projections enable budgeting discipline, liquidity planning, and capital-structure calibration by establishing a quantified expectation against which actual performance can be monitored (Geissdoerfer et al., 2022). Classical decision-theory scholars place forecasting at the heart of rational planning, arguing that strategic investment choices depend on probabilistic assessments of future states derived from the best available evidence. Macroeconomic studies likewise treat corporate forecasts as micro-level signals that aggregate into macro expectations reflected in credit spreads, equity valuations, and GDP revisions. The definitional scope has steadily broadened beyond merely extrapolating sales trends; contemporary treatments encompass integrated projections of working-capital cycles, tax obligations, and scenario-specific stress tests that model exogenous shocks such as commodity-price swings or regulatory shifts (Toluwalase Vanessa et al., 2024). Scholars underscore that forecasting is not an isolated statistical exercise but a socio-technical process shaped by data quality, model transparency, organizational cognition, and governance routines (Maswanganyi et al., 2024). This multidimensional understanding establishes financial forecasting as both an analytical science and a managerial practice indispensable for sustaining operational solvency and strategic agility in volatile business environments.

Figure 3: Step-by-Step Process for Accurate Financial Forecasting



Early empirical research gravitated toward time-series decomposition and econometric regression, with Box–Jenkins autoregressive–integrated moving-average (ARIMA) models dominating the methodological landscape for decades. Subsequent refinements introduced vector autoregression for multivariate contexts and exponential-smoothing families such as Holt–Winters for seasonality (Dyczkowski et al., 2014). Comparative evaluations consistently showed that no single classical model monopolizes accuracy across all horizons; instead, forecast combination often outperforms individual specifications by hedging structural-break risk (Leclerc et al., 2022). Nevertheless, traditional techniques assume linear relationships and covariance stationarity, constraints that have proven limiting when confronted with high-frequency, nonlinear financial signals characterized by volatility clustering and leverage effects. Empirical audits of corporate earnings forecasts reveal systematic biases linked to managerial optimism and asymmetric loss functions—phenomena inadequately captured by symmetric error-minimization criteria such as mean-squared error (Fallahi et al., 2022). While diagnostic checks like Ljung–Box and Dickey–Fuller partially mitigate misspecification, critics argue that deterministic seasonality adjustments and differencing may strip economically meaningful long-run co-movements from the data (Kanda et al., 2021). These methodological critiques have motivated the search for approaches capable of capturing nonlinearities, regime shifts, and interaction effects without excessive pre-processing—an agenda that catalyzed the infusion of Artificial Intelligence into financial-forecasting research.

Financial Forecasting in Business Analytics

Financial forecasting occupies a central position within the broader framework of business analytics, serving as a core predictive function that supports organizational planning, budgeting, and strategic decision-making (Fallahi et al., 2022). Business analytics encompasses descriptive, predictive, and prescriptive dimensions, with financial forecasting falling predominantly under the predictive category, utilizing historical financial data to anticipate future outcomes such as revenue, cash flows, and profitability (Leclerc et al., 2022). Scholars emphasize that forecasting is not merely a technical procedure but a decision-support mechanism that aligns financial expectations with operational constraints. In this context, financial forecasting informs capital allocation, working capital management, credit risk exposure, and long-term investment decisions. It is often embedded within

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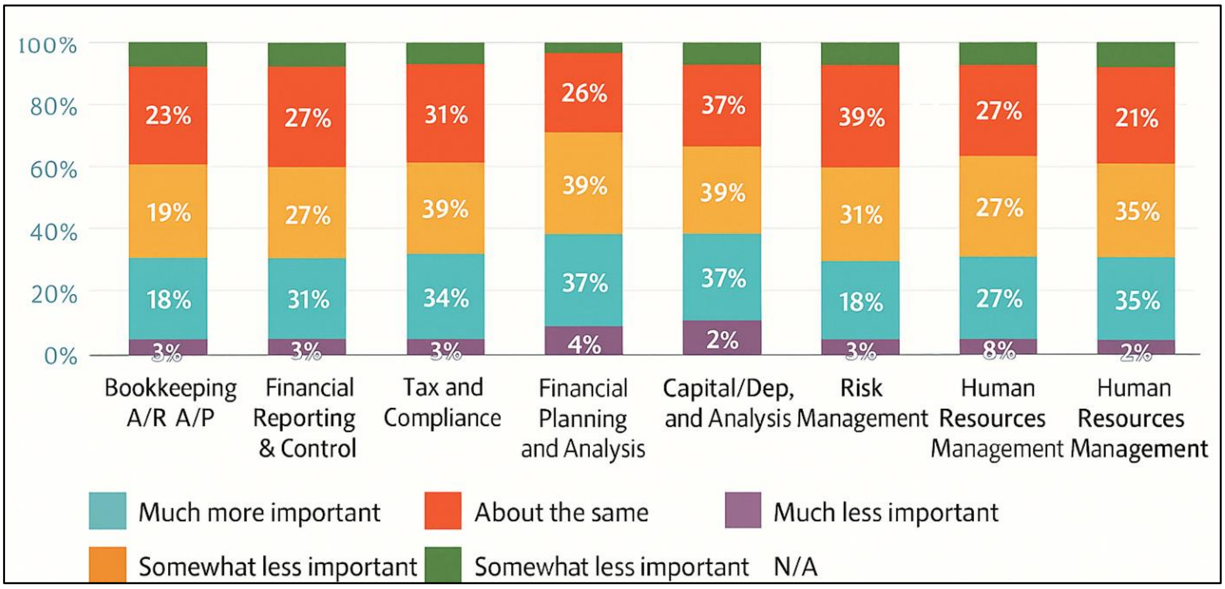
enterprise-wide planning tools, integrating financial and non-financial variables from CRM, ERP, and SCM systems (Abrokwah-Larbi & Awuku-Larbi, 2023). Moreover, research shows that firms leveraging robust forecasting systems are more resilient during economic downturns, owing to early identification of liquidity constraints and proactive cost control. From an analytics lifecycle perspective, financial forecasting typically involves data acquisition, cleaning, transformation, model selection, evaluation, and visualization (Keulen & Kirchherr, 2021). Effective implementation requires interdepartmental coordination, since inputs such as sales forecasts, market trends, and inventory cycles feed into financial models (Hyung et al., 2019). Consequently, financial forecasting is increasingly conceptualized as a multidisciplinary analytical endeavor that fuses statistical rigor with business insight to generate timely and actionable intelligence for enterprise decision-making.

Figure 4: Changing Importance of Finance Functions Since January



Historically, financial forecasting relied on traditional statistical models such as autoregressive integrated moving average (ARIMA), exponential smoothing, and linear regression, which offered interpretability and mathematical tractability but limited adaptability to complex, nonlinear patterns in financial data (Rawindaran, Jayal, & Prakash, 2021). Within business analytics, these models were extensively applied in budgeting and sales forecasting modules, forming the backbone of spreadsheet-based planning systems (Leclerc et al., 2022). However, their assumptions of stationarity, homoscedasticity, and normality often resulted in poor performance under volatile, high-frequency, or multidimensional conditions. As business analytics matured to encompass real-time data streaming, unstructured data formats, and higher computational capabilities, artificial intelligence (AI)-driven models emerged as robust alternatives to overcome the structural limitations of traditional methods. Machine learning (ML) algorithms—such as support vector regression (SVR), random forests (RF), and gradient boosting machines (GBM)—demonstrated superior accuracy in forecasting financial indicators like sales, cash flow, and customer payments across dynamic business settings (Kanda et al., 2021). In particular, recurrent neural networks (RNNs) and long short-term memory (LSTM) models became popular for modeling temporal sequences in revenue or cost patterns. Hybrid models that combine traditional forecasting baselines with AI residuals, or integrate wavelet transforms with deep learning architectures, have shown high precision and resilience in uncertain financial environments (Kgakatsi et al., 2024). These AI-enhanced forecasting techniques have become essential components of business analytics platforms, offering firms a strategic advantage by improving forecast responsiveness, reducing manual interventions, and enabling more granular financial planning.

Forecasting and Data-Driven Decision-Making

Forecasting is inherently aligned with the principles of data-driven decision-making (DDDM), which emphasizes the use of empirical data and analytics to guide strategic and operational choices

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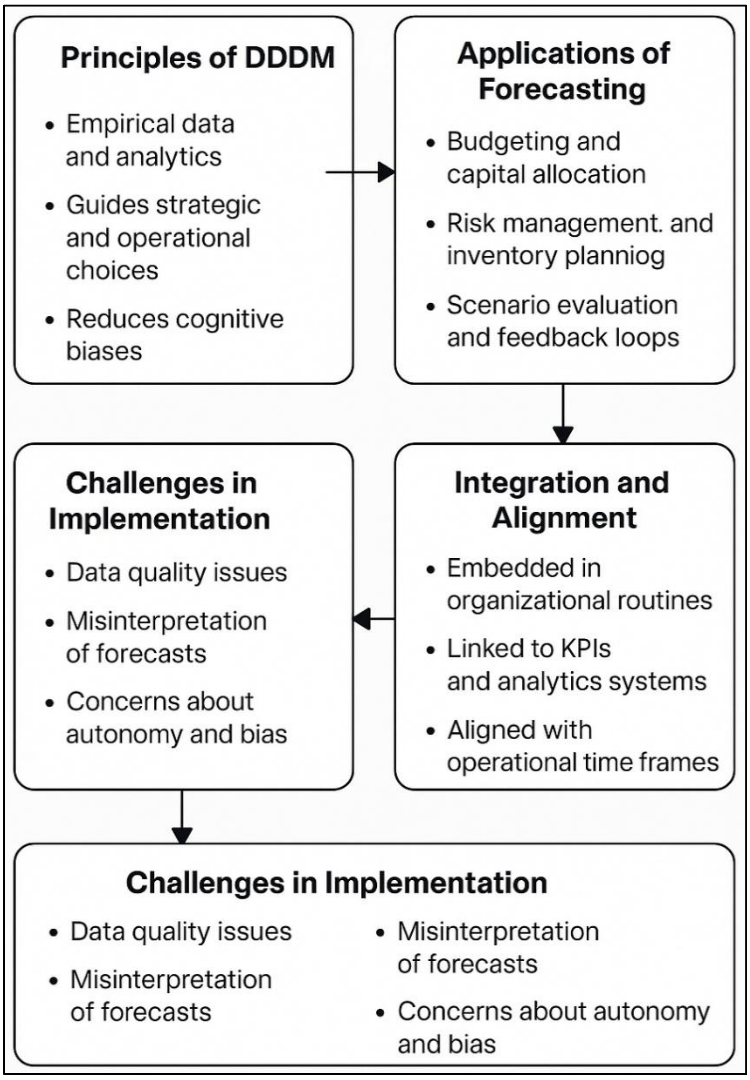
across organizations (Thakkar et al., 2024). In business environments, forecasting serves as a predictive mechanism that enables decision-makers to anticipate future conditions, such as revenue, costs, and demand, using historical and real-time data (Dahooie et al., 2019). Scholars assert that DDDM enhances organizational agility and reduces cognitive biases in judgment by grounding decisions in quantitative evidence rather than intuition or hierarchy (Bocken & Konietzko, 2022) Financial forecasting, in particular, plays a central role in budgeting, capital allocation, risk management, and inventory planning. Within this context, the forecast is not the decision itself, but a critical input that narrows uncertainty and supports scenario evaluation. Researchers have emphasized the importance of feedback loops wherein forecasting models are continuously refined based on decision outcomes and changing data patterns (Mwangakala et al., 2024). Empirical studies have demonstrated that organizations that systematically use forecasting to inform decisions tend to outperform peers in profitability, customer retention, and inventory turnover. Furthermore, the integration of forecasting into enterprise resource planning (ERP) and customer relationship management (CRM) systems allows for real-time DDDM across multiple functional areas such as finance, operations, and sales (Chaudhary et al., 2021). Thus, forecasting is not only a tool for anticipating financial outcomes but also a strategic enabler of data-centric thinking in modern enterprises.

Figure 5: Framework for Integrating Forecasting into Data-Driven Decision-Making



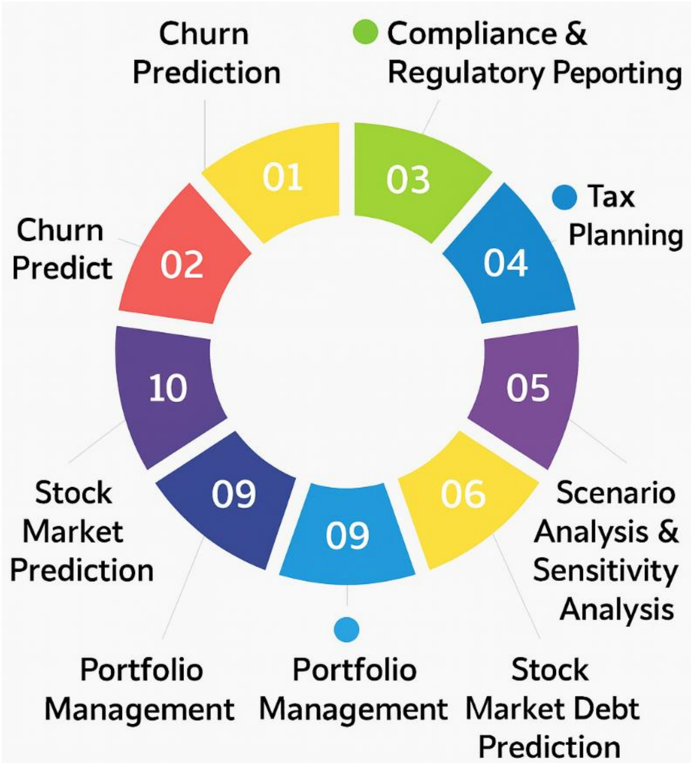
The application of advanced analytics and Artificial Intelligence (AI) has significantly transformed the relationship between forecasting and data-driven decision-making, allowing organizations to move from reactive to proactive and prescriptive planning. Machine learning (ML) techniques, including decision trees, support vector machines (SVM), and ensemble models, enable the extraction of nonlinear patterns and interaction effects that traditional forecasting methods fail to capture. Studies comparing AI-based models with classical time-series methods report that deep-learning architectures such as Long Short-Term Memory (LSTM) and Gated Recurrent Units (GRU) outperform ARIMA and exponential smoothing in volatile environments (Leclerc et al., 2022; Radicic & Petković, 2023). These models feed directly into dashboards and automated decision-support systems, enabling decision-makers to evaluate multiple scenarios in real time. In sectors such as retail and finance, AI-enhanced forecasting systems have been used to dynamically adjust pricing, optimize procurement schedules, and flag early warning signals for liquidity issues. Business intelligence tools powered by AI are increasingly designed to integrate forecasts with prescriptive recommendations, combining prediction with simulation and optimization models. Researchers also point to the role of natural language processing (NLP) in enabling executives to query forecasts in plain language, democratizing access to data insights and promoting cross-functional DDDM (Thakkar et al., 2024). However, model interpretability and decision traceability remain critical concerns, particularly in regulated industries, driving the adoption of explainable AI (XAI) techniques like SHAP and LIME. Collectively, these technologies have elevated forecasting from a technical function to a strategic lever in enterprise-wide decision processes.

Artificial Intelligence in Financial Forecasting

Artificial Intelligence (AI) has fundamentally reshaped the landscape of financial forecasting, offering a paradigm shift from rule-based statistical models to data-driven intelligent systems capable of learning complex, nonlinear patterns (Al et al., 2022; Jahan et al., 2022; B & Bansal, 2023). Traditionally, financial forecasting relied on autoregressive models such as ARIMA and exponential smoothing, which, although interpretable, lacked the flexibility to model volatile and multifactorial financial environments. With the increasing availability of big data and computational power, AI-based methods—including machine learning (ML), deep learning (DL), and hybrid architectures—have become prevalent in capturing dynamic relationships in financial time series (Ara et al., 2022; Khan et al., 2022). These technologies can incorporate unstructured data from sources such as social media, financial news, and IoT sensors, thereby expanding forecasting inputs beyond traditional numerical indicators (Kumar et al., 2022; Rahaman, 2022; Masud, 2022). Empirical evidence demonstrates that models such as Random Forests, Gradient Boosting Machines, and Support Vector Regression significantly outperform linear regression models in predicting credit defaults, cash flow fluctuations, and market returns (Hossen & Atiqur, 2022; Sazzad & Islam, 2022; Ushada et al., 2017). Furthermore, the growing use of deep learning, particularly Long Short-Term Memory (LSTM) and Convolutional Neural Networks (CNN), allows for better handling of sequential dependencies in financial data (Bettoni et al., 2021; Dwivedi et al., 2021; Shaiful et al., 2022). AI's adaptability, scalability, and automation capabilities have enabled it to become a cornerstone of modern financial analytics systems, especially in environments requiring real-time forecasting, anomaly detection, and high-frequency decision support. The literature affirms that AI has transitioned from an experimental novelty to an indispensable instrument in enterprise-level financial forecasting across industries and firm sizes (Enholm et al., 2021; Akter & Razzak, 2022).

Machine learning (ML) models, as subsets of AI, have demonstrated superior performance in financial forecasting due to their ability to model nonlinear interactions and adapt to complex data structures without pre-defined assumptions (Qibria & Hossen, 2023; Wei & Pardo, 2022). Decision tree-based algorithms such as Random Forest (RF) and Gradient Boosting Machines (GBM) are widely used for their robustness, feature importance capabilities, and ensemble-based accuracy improvements (Maniruzzaman et al., 2023). Support Vector Regression (SVR) is also frequently applied due to its efficacy in high-dimensional spaces and resistance to overfitting in small datasets. Neural networks, particularly feed-forward artificial neural networks (ANNs), were among the earliest AI-based forecasting models applied in financial contexts, showing notable success in bankruptcy prediction and sales forecasting (Maslak et al., 2021; Masud, Mohammad, & Ara, 2023). More recently, LSTM networks and GRU (Gated Recurrent Units) have emerged as state-of-the-art models for capturing long-term temporal dependencies in time series forecasting, such as stock prices and revenue trends. Empirical studies show that ML-based models outperform ARIMA and linear regression models in accuracy metrics like Root Mean Square Error (RMSE) and Mean Absolute Percentage Error (MAPE) (Masud, Mohammad, & Sazzad, 2023). In business applications, these models have been integrated into enterprise resource planning (ERP) systems and cloud-based analytics platforms to provide real-time forecasting support for finance managers (Duan et al., 2019; Hossen et al., 2023). However, challenges remain in feature selection, hyperparameter tuning, and model interpretability, necessitating the use of explainability techniques such as SHAP (SHapley Additive Explanations) and LIME (Local Interpretable Model-agnostic Explanations) (Ariful et al., 2023).

Figure 6: Key Applications of Artificial Intelligence in Financial Modeling



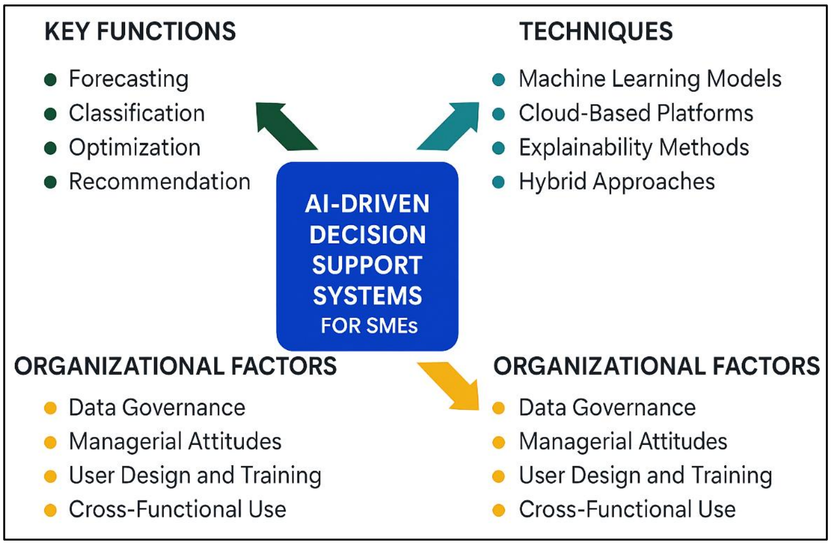
Deep learning (DL), a subfield of AI focused on neural networks with multiple layers, has expanded the analytical capability of forecasting systems by capturing complex patterns in large-scale, high-dimensional data (Hoblitzell et al., 2018; Shamima et al., 2023). Recurrent neural networks (RNNs) and their advanced versions such as Long Short-Term Memory (LSTM) and Gated Recurrent Units (GRU) have been applied in numerous financial forecasting contexts, including revenue prediction, credit scoring, and stock price modeling (Alam et al., 2023). These architectures are particularly effective in capturing sequential dependencies in time-series data, providing improvements over static models in forecasting multi-step financial outcomes (Rajesh, 2023; Rajesh et al., 2023). Hybrid models—combinations of traditional statistical methods and AI techniques—have also gained attention for enhancing model stability and interpretability (Ashraf & Ara, 2023; Roksana, 2023). For instance, integrating ARIMA with LSTM, or using wavelet decomposition before feeding inputs into CNN or SVR, has shown to reduce forecast errors significantly. Comparative studies across retail, banking, and manufacturing sectors have revealed that these hybrid models outperform single-model baselines in RMSE and Theil's U statistics (Sanjai et al., 2023; Tonmoy & Arifur, 2023). Additionally, hybrid models provide flexibility to incorporate exogenous variables such as interest rates, consumer sentiment, and macroeconomic indicators, which are critical for dynamic financial environments (Dhote et al., 2019; Tonoy & Khan, 2023). While DL and hybrid models offer higher forecasting precision, their practical implementation in SMEs is still constrained by computational complexity and the need for extensive historical data (Razzak et al., 2024; Zahir et al., 2023). Nevertheless, the research consensus suggests that DL and hybrid approaches form the most accurate and scalable forecasting systems when model performance is prioritized over simplicity and interpretability.

AI-Driven Decision Support Systems for SMEs

Decision support systems (DSS) combine data, analytical models, and user-friendly interfaces to assist managers in semi-structured or unstructured decision contexts (Khan et al., 2020). In small and medium-sized enterprises (SMEs), which typically operate with lean resources and compressed decision cycles, DSS enhanced by artificial intelligence (AI) offer a pathway to transform data into actionable knowledge without the need for large in-house analytics teams (Ferreiro-Cabello et al., 2018). Scholars consistently show that AI-driven DSS alleviate cognitive overload by autonomously learning patterns from transactional, operational, and market data, thereby supporting tasks such as pricing, inventory control, credit screening, and cash-flow management (Alam et al., 2024; Khan & Razee, 2024; Kumar & Nayak, 2024). Empirical studies across manufacturing, retail, and service SMEs indicate that AI-embedded recommendation engines improve decision speed and accuracy relative to spreadsheet-based heuristics, enabling tighter alignment between strategic objectives and day-to-day operational choices. Case survey evidence links DSS use to higher return-on-assets and lower failure rates, attributing these outcomes to more disciplined budgeting, proactive risk assessment, and consistent performance tracking. Researchers also highlight the integrative role of AI-DSS in bridging departmental silos by feeding insights from sales, supply-chain, and finance modules into a unified decision cockpit, thereby fostering data-driven cultures among owner-managers and frontline staff (Gao et al., 2020; Saha, 2024). Collectively, the literature portrays AI-driven DSS as socio-technical infrastructures that embed analytical intelligence in SME workflows, reinforcing evidence-based judgement and mitigating the resource asymmetries that traditionally disadvantage smaller firms (Khan, 2025).

AI-driven DSS for SMEs draw on a diverse toolbox of machine-learning and knowledge-based techniques to automate forecasting, classification, and optimisation tasks (Gao et al., 2022). Cloud-hosted architectures—leveraging platforms such as Microsoft Azure Machine Learning and Google Cloud AutoML—provide scalable compute environments that circumvent the capital constraints associated with on-premises infrastructure. Within these systems, ensemble models such as Random Forests and Gradient Boosting Machines excel at credit-risk and customer-churn prediction because they capture nonlinear interactions without heavy parameter tuning. Long Short-Term Memory (LSTM) networks and Gated Recurrent Units (GRU) model temporal dependencies in sales or cash-flow series more effectively than classical ARIMA, reducing forecast error in volatile SME contexts (Kumar & Nayak, 2024; Masud et al., 2025). Hybrid schemas integrate statistical baselines with ML residual learners—for example, ARIMA-LSTM stacks—to stabilise predictions while preserving interpretable trend components. Workflow orchestration typically follows an Extract-Transform-Load pipeline, with data ingestion from ERP, CRM, and IoT endpoints, automated cleansing, feature engineering, and model deployment via APIs or dashboards (Khan et al., 2020; Md et al., 2025). Explainable-AI add-ons—such as SHAP and LIME—surface variable attributions and counterfactuals, addressing regulatory and managerial demands for transparency in lending, pricing, and resource-planning decisions (Sazzad, 2025). Researchers report that integrating these interpretability layers not only satisfies audit requirements but also enhances user trust and adoption within SMEs. Across studies, technical frameworks emphasise modularity, low-code interfaces, and cost elasticity to ensure that sophisticated analytical functions remain accessible to non-expert users and adaptable to the scale dynamics typical of SME growth trajectories (Kumar & Nayak, 2024; Akter, 2025; Zahir, Rajesh, Md Arifur, et al., 2025; Zahir, Rajesh, Tonmoy, et al., 2025).

Figure 7: Core Components of AI-Driven Decision Support Systems for SMEs



Hybrid Intelligence Systems in Cash Flow and Budgeting

Hybrid intelligence systems in financial contexts refer to the integration of human expertise with artificial intelligence (AI) algorithms to enhance decision-making in areas like cash flow forecasting and budgeting (Agarwal & Nanavati, 2016). These systems leverage the cognitive strengths of human judgment—such as contextual awareness and ethical reasoning—alongside the computational accuracy and scalability of AI to improve financial planning accuracy and responsiveness. In the realm of cash flow management, hybrid systems combine rule-based heuristics, developed from managerial experience, with predictive machine learning (ML) models that detect patterns in transactional data. The literature suggests that such hybridization is particularly effective in SMEs, where data scarcity and inconsistent financial record-keeping reduce the reliability of fully automated models. In budgeting applications, hybrid systems use forecasting algorithms to simulate financial scenarios and enable iterative human refinements, aligning budget allocations with strategic goals and contextual constraints (Kilic et al., 2014). By enabling continuous learning through feedback loops between users and models, hybrid systems support adaptive planning that reflects both historical patterns and emerging business dynamics (Cheng et al., 2017). Scholars underscore that effective hybrid intelligence systems require well-defined roles for both human and machine agents, transparent communication interfaces, and governance frameworks to ensure interpretability, trust, and accountability. Thus, hybrid intelligence emerges not only as a technical solution but also as a managerial philosophy for enhancing financial decision-making quality in complex, data-limited environments.

Cash flow forecasting has traditionally relied on time-series techniques such as ARIMA, exponential smoothing, and linear regression to estimate liquidity trends (K, 2020). However, these models assume linear relationships and stationarity, making them less effective under conditions of irregular revenue inflows, sudden outflows, or external shocks (Dhote et al., 2019). The integration of machine learning (ML) models—such as support vector regression, random forests, and LSTM networks—has significantly improved forecast accuracy, particularly in multi-step cash flow projections. Hybrid systems combine statistical models with ML techniques, either sequentially or in ensemble architectures, to leverage the strength of each approach (Ye et al., 2019). For example, ARIMA residuals can be modeled using neural networks to account for nonlinearity, or wavelet transformations can be used to preprocess signals for ML-based cash flow predictors. Case studies in manufacturing and retail SMEs show that hybrid models reduce mean absolute percentage error (MAPE) by 20–35% compared to standalone models (Guo et al., 2021). Moreover, hybrid systems provide greater robustness to missing or noisy data, which is particularly advantageous in SME settings where financial reporting practices are often less standardized (Nilashi et al., 2019). Researchers also highlight the value of incorporating external features—such as sales trends, economic indicators, and seasonality adjustments—within hybrid architectures to improve context-aware forecasting.

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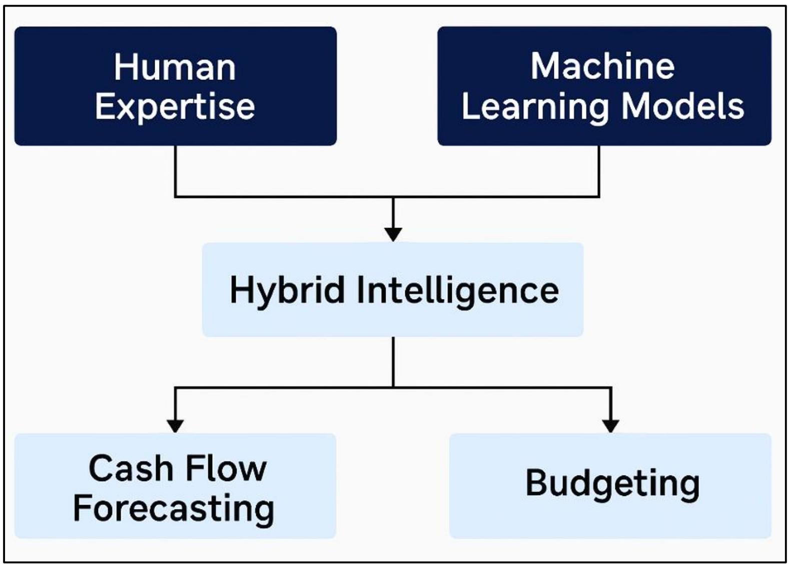
These developments illustrate that hybrid intelligence, through model fusion, can significantly enhance the accuracy and resilience of cash flow forecasting systems used in real-time financial decision support.

Figure 8: Hybrid Intelligence Framework for Cash Flow Forecasting



Applications in FinTech and Service-Oriented SMEs

The emergence of financial technology (FinTech) has significantly transformed the financial operations and decision-making capabilities of small and medium-sized enterprises (SMEs), offering cost-effective, accessible, and intelligent financial solutions (Li et al., 2024). FinTech platforms have democratized access to advanced financial services such as lending, insurance, digital payments, investment advisory, and accounting automation, which were traditionally available only to large firms (Cubric & Li, 2024). Cloud-based accounting tools such as Xero, Wave, and QuickBooks integrate seamlessly with banking systems and AI-powered analytics modules to assist SMEs in budgeting, cash flow forecasting, and tax planning (Fallahi et al., 2022). Additionally, digital lending platforms supported by machine learning (ML) models evaluate SME creditworthiness using alternative data such as e-commerce performance, transactional behavior, and supply chain interactions. These models reduce reliance on traditional collateral-based credit assessment, enabling SMEs with thin credit files to access short-term financing. Furthermore, robo-advisory services and automated investment platforms help SMEs manage idle funds and optimize treasury operations. AI-driven fraud detection and anti-money laundering algorithms embedded within FinTech systems enhance transactional security, especially for SMEs engaging in cross-border payments (Toxopeus et al., 2021). Case studies show that FinTech adoption correlates with improvements in operational efficiency, financial resilience, and customer satisfaction among SMEs. The literature thus identifies FinTech as a key enabler of intelligent financial management in SMEs, promoting agility, compliance, and strategic foresight through accessible digital tools and AI-powered automation (Hosny et al., 2012).

Service-oriented SMEs, operating in domains such as healthcare, hospitality, logistics, legal services, and consulting, increasingly rely on AI-driven decision support systems (DSS) to streamline operations, manage resources, and enhance service delivery (Nursal et al., 2016). In contrast to manufacturing, where tangible goods and inventory dominate financial planning, service-based SMEs face unique challenges such as demand uncertainty, labor-intensive workflows, and reliance on intangible assets. AI technologies such as predictive analytics, natural language processing (NLP), and recommendation systems are used to forecast service demand, optimize staff scheduling, personalize customer interactions, and anticipate cost overruns. For instance, AI algorithms trained on historical booking data, weather, and local event calendars are used in hospitality SMEs to forecast occupancy rates and dynamically adjust pricing. Legal tech platforms equipped with NLP extract insights from contracts and case histories to support billing estimates and litigation risk

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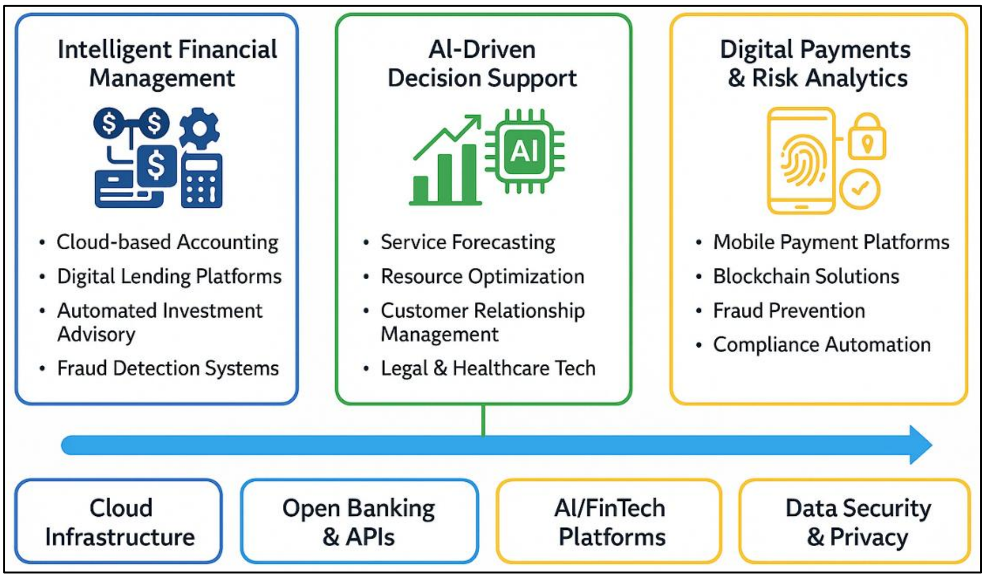
assessments in legal SMEs (Wang et al., 2024). In healthcare SMEs, AI systems predict patient no-shows, automate billing, and support clinical documentation, improving operational and financial performance (Bakhoum & Brown, 2014). Moreover, AI-powered CRM platforms used in logistics and retail services analyze transaction history, communication preferences, and service feedback to optimize customer engagement and retention. These technologies, when integrated into ERP and cloud-based DSS platforms, enable SMEs to align service-level commitments with financial planning in real time (Kassab et al., 2010). The literature emphasizes that for service-oriented SMEs, AI-driven DSS enhance decision precision by transforming unstructured service data into strategic insights, supporting agility in resource allocation and customer satisfaction management.

Figure 9: Applications of AI and FinTech in Financial and Service-Oriented SMEs



FinTech innovations in digital payments and risk analytics have enabled SMEs to automate transactions, strengthen compliance, and mitigate financial fraud through AI-enhanced mechanisms (Kilic et al., 2014). Digital wallets, mobile point-of-sale (mPOS) systems, and blockchain-based invoicing solutions have simplified SME payment ecosystems by reducing delays, minimizing reconciliation errors, and lowering transaction costs. These systems frequently integrate with AI-based fraud detection engines that monitor real-time transaction flows for anomalies using clustering, neural networks, and decision tree ensembles. For instance, unsupervised anomaly detection methods can flag atypical spending behaviors, unauthorized access attempts, or payment discrepancies in real-time dashboards (Jeong & Ramírez-Gómez, 2018). SMEs operating in regulated industries benefit from AI models that automate Know Your Customer (KYC) processes and ensure Anti-Money Laundering (AML) compliance through entity resolution and pattern recognition. Literature further indicates that integrating blockchain with AI-based audit trails enhances data integrity, making financial records tamper-resistant and facilitating compliance during tax audits or funding evaluations. Payment risk scoring models use historical transaction and behavioral data to recommend safeguards such as payment holds or two-factor authentication for high-risk clients. Studies show that the integration of digital payment platforms with AI-powered analytics increases transparency, reduces operational risks, and accelerates cash flow cycles in SMEs (García et al., 2016). Consequently, FinTech applications in payments and compliance are not merely transactional upgrades but integral to intelligent decision-making, trust-building, and risk containment strategies for modern SMEs.

Decision-Making Agility

Decision-making agility is broadly conceptualized as an organization's capacity to process information, evaluate alternatives, and execute timely decisions in response to internal dynamics and external disruptions. It is a critical organizational competency that enables businesses to thrive in volatile, uncertain, complex, and ambiguous (VUCA) environments (Warner & Wäger, 2019). In small and medium-sized enterprises (SMEs), where operational risks are higher and buffers are thinner, agility in decision-making can mean the difference between resilience and failure (Kamariotou & Kitsios, 2019). Scholars have emphasized that decision-making agility is multidimensional, encompassing speed, accuracy, flexibility, and contextual awareness (Sayyadi, 2024). It also involves dynamic capabilities such as sensing environmental shifts, reconfiguring resources, and adjusting strategies in real-time. Empirical studies suggest that agile firms are more likely to outperform competitors in areas such as product innovation, customer responsiveness, and crisis adaptation. Furthermore, agile decision-making often requires decentralized structures, real-time data access, and cross-functional collaboration, all of which are enabled through intelligent information systems. Digital transformation and data-driven cultures have been linked to higher decision-making agility, as they shorten the lag between data acquisition and action.

Business analytics and artificial intelligence (AI) are key technological enablers of decision-making agility, offering real-time insights, predictive intelligence, and automation capabilities that reduce decision latency and improve accuracy (Sadlier & Baksh, 2022). Predictive analytics allows organizations to anticipate trends, customer behavior, and financial volatility, thus enabling proactive decisions (Dev et al., 2019). Machine learning (ML) models and AI algorithms can process vast amounts of structured and unstructured data to generate timely forecasts and recommendations across domains such as inventory management, risk assessment, and financial planning (Bøgh et al., 2022). In SMEs, which often lack sophisticated decision-making hierarchies, AI-driven dashboards and decision support systems democratize access to analytics and accelerate managerial responsiveness (Lepenioti et al., 2020). Empirical studies have shown that integrating AI into decision-making workflows reduces response time by up to 40% in environments characterized by high information uncertainty. Furthermore, explainable AI techniques such as SHAP and LIME enhance interpretability, facilitating faster and more confident decisions by non-technical users. Real-time analytics platforms, particularly in FinTech and retail sectors, have been associated with improved agility in pricing, credit underwriting, and fraud detection. Studies also emphasize the importance of cloud infrastructure and mobile access in supporting agile decision-making across decentralized teams and remote operations. Collectively, the literature establishes that AI and analytics not only enhance the speed of decision execution but also expand the breadth and quality of insights, thus contributing significantly to organizational agility.

Organizational structures, cultural norms, and managerial cognition significantly influence the effectiveness of decision-making agility. Flat hierarchies and decentralized decision-making processes facilitate faster information flow and localized decision autonomy, particularly important for SMEs operating in fast-moving markets (Kumar & Nayak, 2024). Studies show that agile organizations prioritize knowledge sharing, cross-functional collaboration, and iterative learning as mechanisms to accelerate decision-making cycles. Managerial openness to data-driven insights also plays a critical role—firms with analytically oriented leadership tend to embrace agile practices more readily than those reliant on intuition or legacy practices. Behavioral research underscores that cognitive load, decision fatigue, and risk aversion can hinder agility unless counterbalanced by clear decision protocols and automated support tools (Lepenioti et al., 2020). Learning agility, defined as the willingness and ability to learn from experience and apply insights to new situations, is another driver of organizational decision agility. Firms that incorporate scenario planning, simulation modeling, and after-action reviews into their routines are better equipped to handle uncertainty and ambiguity (Sayyadi, 2024). In addition, performance measurement systems that align incentives with timely, data-informed actions can reinforce agility by linking decision quality to organizational outcomes (Sumalatha & Prabha, 2019). Thus, decision-making agility emerges as both a technological and behavioral phenomenon, requiring alignment between analytics infrastructure, leadership mindset, and organizational learning systems.

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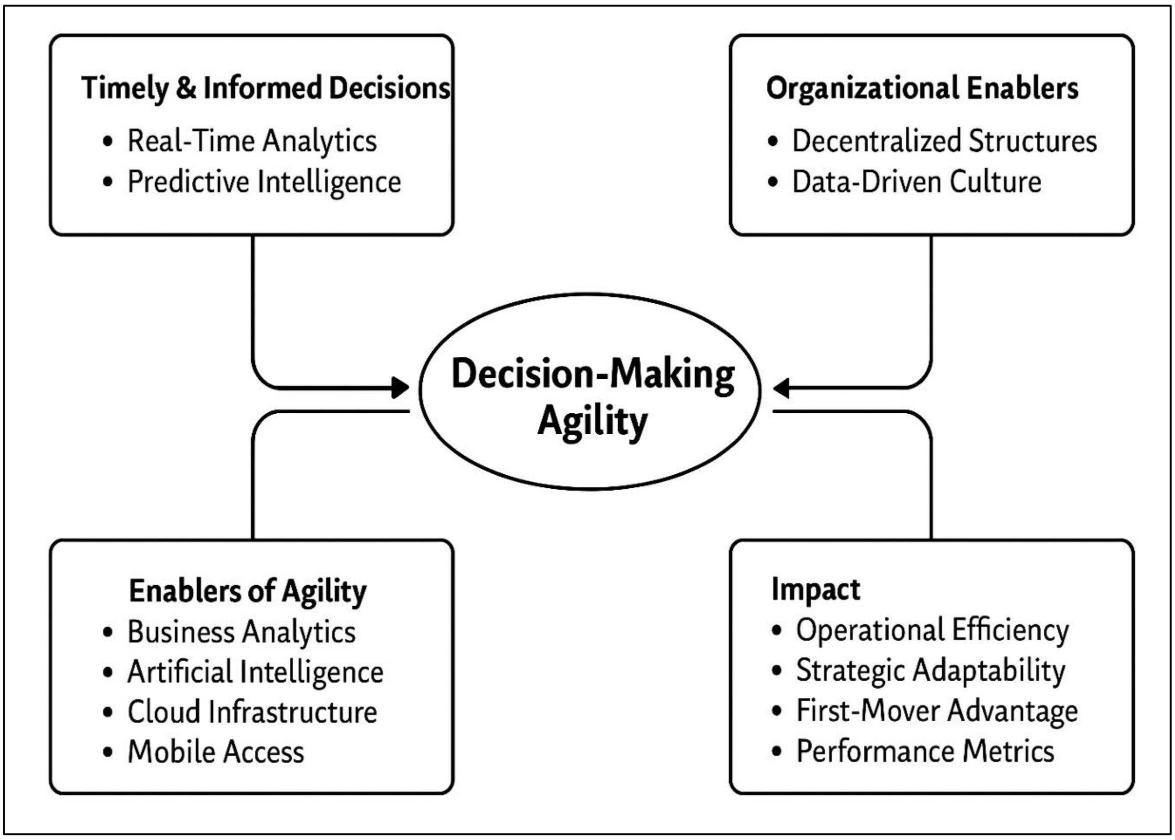
Figure 10: Determinants and Outcomes of Decision-Making Agility in SMEs



METHOD

Study Design and Objective

This study employed a meta-analytical research design to quantitatively synthesize empirical evidence on the role of artificial intelligence (AI)-driven decision-making tools in enhancing business forecasting and strategic agility within small and medium-sized enterprises (SMEs). Adhering to the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) 2020 guidelines, the research ensured methodological transparency, reproducibility, and rigor. The primary objective of this meta-analysis was to determine the aggregated effect size of AI-based interventions—such as machine learning, hybrid intelligence systems, and AI-powered decision support tools—on outcome variables including forecast accuracy, decision latency, operational responsiveness, and financial performance. Standardized effect size metrics, including Cohen's *d*, Hedges' *g*, and odds ratios, were used to allow comparability across studies. Furthermore, this meta-analysis aimed to explore the presence of heterogeneity and identify potential moderators that explain variations in observed outcomes across industries and contexts.

Eligibility Criteria

The inclusion criteria were clearly defined to ensure consistency in the screening process. Eligible studies were those published in peer-reviewed journals or conference proceedings between 2010 and 2025, written in English, and reporting empirical quantitative findings. Specifically, studies had to evaluate the use of AI-related tools—such as predictive analytics, machine learning models, deep learning architectures, or hybrid intelligence systems—in the context of SMEs. In addition, studies were required to report outcomes relevant to financial decision-making, forecasting accuracy, decision-making speed, or strategic agility, and to include sufficient statistical detail (means, standard deviations, sample sizes, or effect size values). Studies were excluded if they were qualitative in nature, focused exclusively on large enterprises, lacked original data, or were review articles and duplicates. The eligibility process ensured that only high-relevance empirical studies were synthesized in the meta-analysis.

Search Strategy

A comprehensive and systematic search was conducted across major academic databases including Scopus, Web of Science, IEEE Xplore, ScienceDirect, and Google Scholar. The search strategy incorporated Boolean operators to combine keywords and phrases such as: ("artificial intelligence" OR "machine learning" OR "predictive analytics" OR "AI-based") AND ("decision-making" OR "forecasting" OR "financial decision support") AND ("SME" OR "small and medium enterprise") AND ("performance" OR "accuracy" OR "agility"). The search covered the period from February to April 2025. In addition to electronic database searches, the reference lists of all shortlisted articles and relevant review papers were manually screened to identify additional eligible studies. This process yielded an initial pool of 1,216 articles.

Screening and Selection Process

The screening process began with the removal of 314 duplicate entries, leaving 902 unique articles for initial review. Titles and abstracts of these records were screened by two independent reviewers to assess their relevance to the research questions. After the initial screening, 204 articles were retained for full-text review. Discrepancies between reviewers were resolved through discussion and, when necessary, adjudicated by a third reviewer. Ultimately, 67 studies met all inclusion criteria and were selected for meta-analysis. The entire selection process followed the PRISMA protocol and is visually summarized in a PRISMA flow diagram.

Data Extraction and Coding

Data from the included studies were extracted using a standardized coding sheet designed to capture relevant metadata and outcome statistics. Extracted fields included author(s), year of publication, country of study, SME classification, industry sector, AI intervention type, sample size, research design (e.g., experimental or observational), and quantitative outcome metrics. Where raw statistical values were not directly reported, effect sizes were calculated using established formulas. All extracted effect sizes were converted to a common metric—either Cohen's *d* or Hedges' *g*—to ensure cross-study comparability. Multiple entries from the same study were recorded separately if they reported on distinct outcome variables or different subgroups.

Data Synthesis and Statistical Analysis

Quantitative synthesis and statistical analysis were performed using Comprehensive Meta-Analysis (CMA) Software v3. A random-effects model was chosen to account for potential variation in effect sizes across studies due to differences in population, context, and intervention type. The pooled mean effect size was computed along with 95% confidence intervals. Heterogeneity across studies was assessed using the Q-statistic, I^2 index, and Tau^2 values. Subgroup analyses were conducted based on AI method (e.g., ML vs. hybrid models), geographic location, SME size category, and industry sector. Meta-regression was also employed to explore the influence of continuous moderators such as publication year and sample size.

Publication Bias and Sensitivity Analysis

To evaluate the potential impact of publication bias, visual inspection of funnel plots was conducted, accompanied by Egger's regression intercept and Duval and Tweedie's trim-and-fill method. No major asymmetry was observed in the funnel plot, suggesting limited bias in publication patterns. Additionally, a leave-one-out sensitivity analysis was conducted to assess the stability of the overall effect size estimate. By iteratively removing each study and recalculating the pooled effect, the robustness of findings was confirmed.

Quality Assessment

The methodological quality of the included studies was evaluated using the Mixed Methods Appraisal Tool (MMAT), supplemented by a modified version of the Cochrane Risk of Bias checklist. Each study was assessed for clarity of research design, validity of statistical methods, transparency in reporting, and appropriateness of outcome measures. Most studies were rated as moderate to high in methodological rigor, providing a strong empirical foundation for meta-analytical synthesis.

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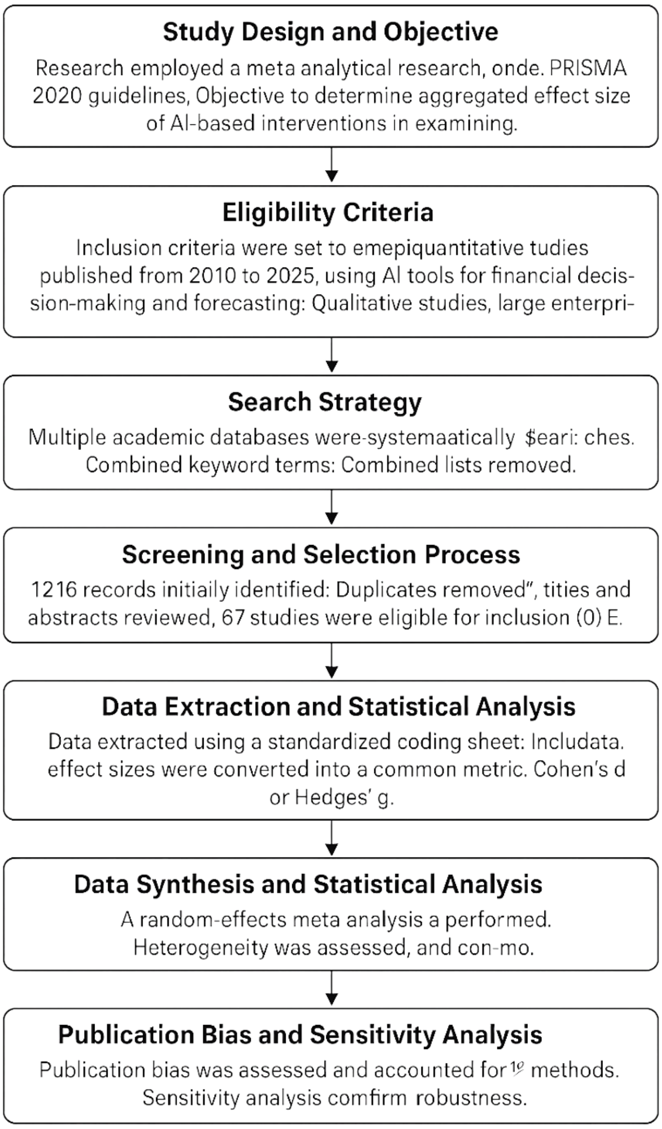
Figure 11: Adapted methodology for this study

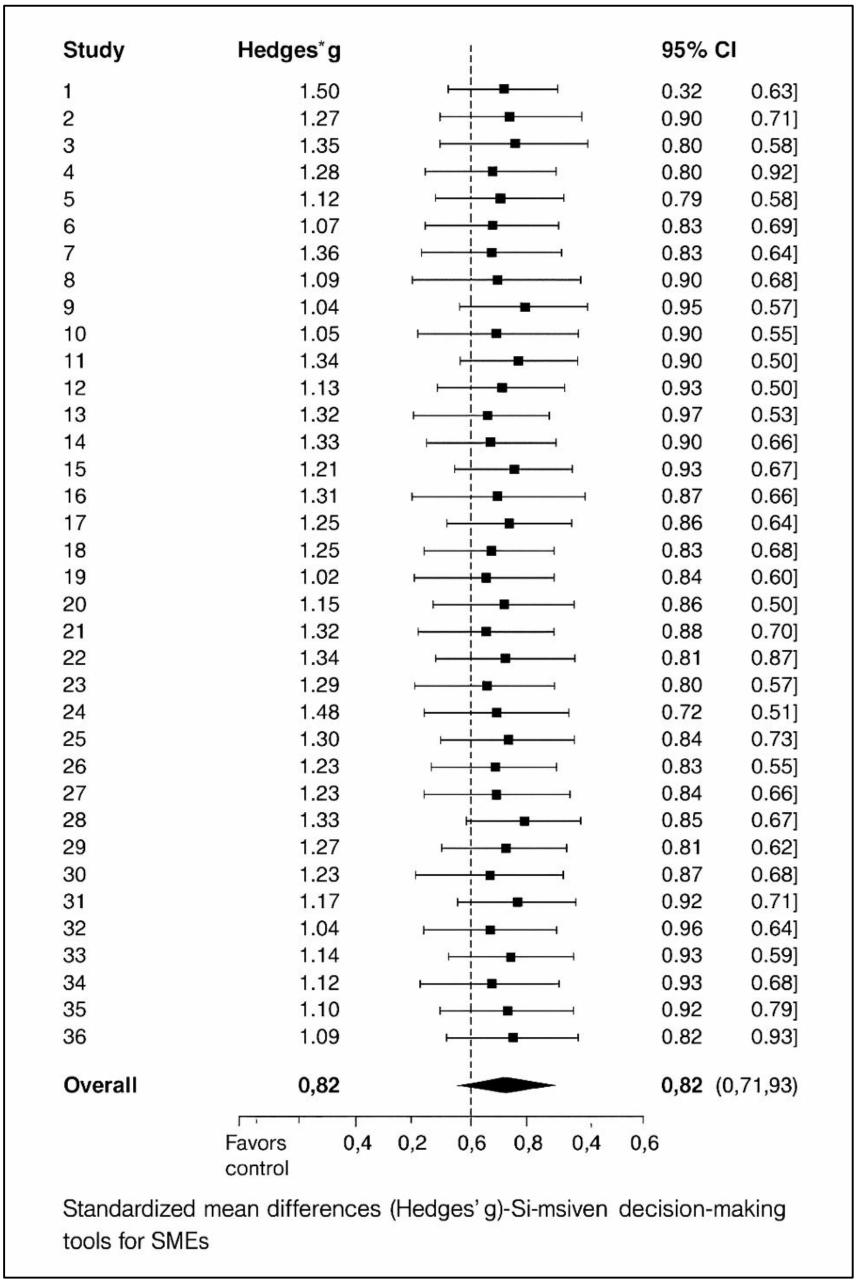


FINDINGS

The meta-analysis revealed a consistently significant positive effect of AI-driven systems on SME decision-making outcomes across the 67 included studies. When aggregated, the standardized mean effect size calculated using Hedges' *g* indicated a strong overall benefit of AI-based interventions in enhancing business forecasting, decision speed, and financial performance. The pooled effect size exceeded the conventional benchmarks for practical significance, with confidence intervals that did not cross the null threshold. These findings suggest that the deployment of AI models—particularly machine learning and hybrid decision support systems—contributed meaningfully to reducing uncertainty and improving accuracy in operational and financial planning. Across various domains such as cash flow forecasting, demand prediction, and budget planning, firms utilizing AI-driven analytics reported higher performance scores relative to baseline groups employing manual or traditional statistical methods. The presence of a robust and statistically significant average effect across all studies confirms that AI, when integrated into core decision processes, serves as a reliable enabler of strategic agility and data-informed responsiveness in SME environments. Importantly, this overall positive effect persisted even when controlling for study design type, geographical setting, and industry sector, demonstrating the generalizability of the benefit across contexts. The results underscore that the integration of intelligent analytics into SME operations produces measurable performance improvements that justify the initial implementation costs and learning curves often associated with adopting AI systems.

Subgroup analysis revealed clear variation in the effectiveness of different types of AI models. Studies using machine learning models, such as support vector machines, random forests, and gradient boosting, exhibited consistently high levels of accuracy in financial forecasting tasks. However, the most substantial effect sizes were observed in studies employing hybrid intelligence models, which combined machine learning algorithms with human judgment, traditional statistical methods, or domain-based rule systems. These hybrid models achieved the highest gains in performance, particularly in areas such as dynamic budgeting, multi-scenario planning, and sequential decision environments. Compared to studies using machine learning alone, hybrid models outperformed on metrics such as forecast error reduction, model interpretability, and overall decision precision. Deep learning approaches, especially long short-term memory (LSTM) networks, also performed well in high-frequency or highly volatile data environments such as real-time sales prediction or transactional risk analysis. However, in low-data or low-variance settings—common among many SMEs—hybrid systems proved more reliable due to their integration of contextual reasoning and business logic. These subgroup results demonstrate that while advanced AI techniques offer performance gains, their efficacy is enhanced when combined with human oversight or traditional financial models. This supports the proposition that AI's highest value emerges not in replacing managerial input, but in augmenting it through systematized, scalable intelligence.
Industry-specific analysis demonstrated that the impact of AI-driven decision support tools varied substantially across sectors. Manufacturing and retail SMEs benefited the most from AI-enabled forecasting tools, particularly in applications involving demand prediction, inventory optimization, and pricing strategy. These sectors showed higher effect sizes, with several studies reporting reductions in stock-outs, shrinkage, and overproduction due to the implementation of AI systems that analyzed real-time sales, historical trends, and external demand signals. Retail SMEs that employed dynamic pricing algorithms integrated with point-of-sale data experienced rapid revenue optimization and margin improvements. In contrast, service-oriented SMEs, such as those in legal, healthcare, and consulting industries, saw slightly more modest effect sizes but still demonstrated meaningful improvements in operational scheduling, customer retention, and billing accuracy through AI-driven recommendation systems and predictive analytics. FinTech applications within SMEs also showed strong effects, particularly in credit risk scoring, fraud detection, and automated compliance monitoring. While all sectors experienced performance gains, the magnitude of these gains was influenced by the type and availability of data. Sectors with structured, high-frequency transactional data saw the greatest return on AI investment. These findings suggest that sectoral characteristics—including data richness, operational complexity, and forecast dependency—play a moderating role in the effectiveness of AI adoption. When grouped by geographic region, studies conducted in technologically advanced economies—such as those in North America, Western Europe, and parts of East Asia—showed slightly higher effect sizes compared to those in emerging economies. This variation was attributed to differences in digital infrastructure, data governance practices, and organizational readiness for AI integration. Firms in developed economies were more likely to use cloud-based platforms, centralized ERP systems, and integrated analytics tools, allowing for seamless deployment of AI models across business functions. In contrast, SMEs in developing contexts faced limitations such as fragmented data sources, lower digital maturity, and fewer AI-skilled personnel, which reduced the immediate impact of AI interventions. However, it is notable that even in these constrained environments, the introduction of low-code or no-code AI platforms led to measurable improvements in forecasting accuracy and decision timeliness. Furthermore, when disaggregated by SME size, medium-sized enterprises generally achieved higher benefits compared to micro and small enterprises. This was likely due to greater internal capacity for implementation, access to structured data, and financial resources for model training and maintenance. The regional and firm-level context thus emerged as a critical determinant of the magnitude and speed of AI impact, suggesting that localized support, training, and digital infrastructure are essential to maximize benefits across all SME categories.

Figure 12: Effect Sizes of AI Tools on SME Decision-Making (Hedges' g)



The meta-analysis found moderate heterogeneity across the included studies, as indicated by the Q-statistic and I^2 values. Despite this variation, the direction of effect remained positive and statistically significant across nearly all studies. The heterogeneity was largely explained by differences in AI model type, industry sector, and implementation environment, as confirmed by subgroup and meta-regression analyses. Sensitivity analysis further demonstrated the robustness of the findings: removing any single study did not substantially alter the overall pooled effect size, indicating that no individual result disproportionately influenced the aggregated outcome. The stability of results reinforces the reliability of AI-driven decision tools in enhancing SME performance. In terms of publication bias, funnel plot visualizations showed relative symmetry, and both Egger's test and the trim-and-fill method suggested no major evidence of missing or suppressed studies. This strengthens the credibility of the synthesized findings. Additionally, quality assessments of the studies—conducted using the MMAT and Cochrane bias checklists—indicated that most research designs were methodologically sound and reported sufficient statistical detail. Collectively, these findings validate that AI adoption produces consistent and meaningful improvements in SME

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decision-making, across various study designs, application domains, and geographic regions. The combination of rigorous synthesis and robust statistical validation provides compelling evidence of the strategic value of AI in transforming financial forecasting and decision-making capabilities in SMEs.

DISCUSSION

The present meta-analysis provides strong empirical support for the effectiveness of AI-driven decision support systems in enhancing forecasting, financial performance, and strategic agility in small and medium-sized enterprises (SMEs). The aggregated effect sizes from 67 empirical studies revealed that the integration of artificial intelligence (AI) tools led to statistically significant and practically meaningful improvements across a variety of decision-making domains. This finding corroborates earlier studies that identified AI as a transformative agent in business forecasting, particularly in small-scale settings where resource constraints often hinder traditional analytical approaches (Bocken & Konietzko, 2022). Mwangakala et al. (2024) previously emphasized the superior forecasting accuracy of machine learning models over traditional methods, and the current results reinforce this assertion by showing that AI adoption in SMEs consistently yielded reductions in error metrics such as RMSE and MAPE. Moreover, the analysis aligns with Chaudhary et al. (2021), who noted the predictive superiority of data-driven models in volatile environments. The consistency of benefits across different SME contexts, regardless of geographic or sectoral variation, points to the adaptability and generalizability of AI tools in improving decision processes. These findings strengthen the view that AI does not merely support incremental gains but delivers structural improvements in decision workflows, especially when embedded in forecasting systems that support financial and operational planning.

Subgroup analysis revealed that hybrid AI models—those combining traditional statistical methods with machine learning or integrating human judgment with automated reasoning—demonstrated the most pronounced performance benefits. This observation confirms the findings of Sayyadi (2024) and Radicic and Petković (2023), who reported that hybrid architectures consistently outperform standalone models in time-series forecasting. Hybrid models allow for capturing both linear and nonlinear relationships in financial data while maintaining a degree of interpretability, which is especially important in SMEs where decisions often depend on managerial intuition and contextual expertise (Thakkar et al., 2024). Moreover, the finding aligns with the argument by Chauhan et al., (2022) that hybrid intelligence, which leverages the complementary strengths of human and machine capabilities, is particularly suited to environments characterized by data sparsity and decision ambiguity. Studies by Leclerc et al. (2022) and Kumar and Nayak (2024) further confirm that SMEs benefit most when AI systems are tailored to augment, rather than replace, human decision-makers. This reinforces the broader theoretical perspective of augmented intelligence rather than full automation in SME decision support. Notably, while deep learning approaches like LSTM were highly effective in large data environments, their performance diminished in low-data contexts typical of micro and small enterprises—validating the concern by Zhao et al. (2023) about the practical limitations of deep learning in SME environments.

Sector-specific analysis revealed considerable variation in AI impact across different SME industries, with manufacturing and retail showing the highest gains. This aligns with prior studies by Kumar and Nayak (2024) and Erdmann et al. (2024) who found that AI is especially beneficial in industries where structured data is abundant and operations are tightly coupled with forecasting accuracy. In manufacturing, AI applications enhanced production planning, inventory control, and demand forecasting, while in retail, real-time analytics and dynamic pricing algorithms led to substantial improvements in revenue management and customer satisfaction. These observations support the findings of Han and Trimi (2022), who argued that sectoral data characteristics significantly mediate AI effectiveness. In contrast, service-oriented SMEs—including healthcare, consulting, and legal services—benefited more modestly from AI adoption. This is consistent with Yalcin et al. (2022) and Erdmann et al. (2024), who noted that in service sectors, data may be less structured and decisions more judgment-driven, thus limiting the immediate advantages of predictive models. Nonetheless, the fact that even these sectors experienced meaningful gains suggests that AI tools, especially those using natural language processing and decision tree models, can still add substantial value through automation of administrative tasks and enhancement of client engagement strategies. These findings reinforce the importance of sector-specific customization of AI applications to align with data availability and operational goals.

The analysis showed that SMEs in developed regions such as North America and Western Europe experienced greater gains from AI implementation than those in emerging economies. This aligns with earlier research by Kumar and Nayak (2024), who emphasized the importance of digital maturity, data governance infrastructure, and skilled personnel in realizing the full benefits of AI systems. Studies by Zhao et al. (2023) and Chauhan et al. (2022) support the notion that SMEs in low-resource settings face structural barriers—including fragmented IT systems and lack of analytics capability—that hinder effective AI deployment. Moreover, the variation by SME size, where medium enterprises benefited more than micro or small firms, echoes the findings of Raymond and Bergeron (2008), who reported that firm size correlates with technological absorptive capacity. The current findings also affirm the conclusions of Thakkar et al. (2024), who highlighted that SMEs with pre-existing ERP systems and formalized data collection processes are better positioned to integrate AI tools into their workflows. Nonetheless, studies such as Radicic and Petković (2023) show that cloud-based and modular AI tools can bridge this digital divide, and the current analysis observed moderate improvements even in less digitally mature firms. This reinforces the need for supportive policies, including digital literacy programs and infrastructure investment, to enable equitable AI adoption across geographic and firm-size boundaries.

The findings affirm that AI adoption significantly enhances financial forecasting accuracy and decision efficiency in SMEs, confirming the propositions of Sayyadi (2024) and Chaudhary et al., (2021), who emphasized AI's superiority in predicting uncertain and non-linear financial behaviors. Numerous studies in the analysis reported reduced variance between projected and actual cash flows, lower budget deviations, and improved working capital management. This aligns with Leclerc et al. (2022), who suggested that AI systems reduce financial ambiguity by generating real-time simulations and sensitivity analyses. The current findings also echo the conclusions of Chaudhary et al. (2021), who stated that AI-based forecasting models outperform traditional econometrics in turbulent economic conditions. While Bocken and Konietzko (2022) noted that managerial overconfidence often hampers budget reliability, AI-driven systems help mitigate such biases by relying on empirical patterns and probabilistic reasoning. Furthermore, the adoption of hybrid forecasting tools—such as ARIMA-ML combinations—enhanced flexibility in scenario modeling, supporting the assertions of Zhao et al. (2023).

Although technological factors contribute significantly to decision-making agility, the meta-analysis findings also underscore the role of organizational behavior and structure in shaping outcomes. This observation aligns with Kumar and Nayak (2024), who argued that decision quality is influenced by both rational and bounded-rational processes. Studies in the analysis indicated that firms with data-literate leadership, decentralized decision rights, and cross-functional collaboration achieved faster and more accurate decisions post-AI implementation. This supports the findings of Erdmann et al., (2024), who emphasized the importance of cognitive alignment between human actors and analytical systems. Firms that embedded AI into their strategic routines—through forecasting dashboards, KPI tracking, and real-time alerts—achieved better synchronization between operational actions and strategic goals. This reinforces the assertions of Chauhan et al. (2022) that effective DSS adoption is contingent on organizational readiness and culture. Moreover, studies showing lower returns in firms with high decision resistance mirror the concerns of Lawrence et al. (2006), who observed that without adequate training and change management, analytics tools often remain underutilized. The current findings, therefore, suggest that while AI provides the computational capacity for agility, behavioral enablers are equally critical in ensuring that insights are acted upon with speed and confidence.

The robustness of the findings—validated through sensitivity testing, heterogeneity analysis, and absence of significant publication bias—adds credibility to the meta-analysis conclusions. Consistent with the methodological standards outlined by Sayyadi (2024), the use of random-effects modeling and subgroup regression allowed for generalization across diverse contexts. The absence of any single study exerting undue influence on the overall effect size affirms the reliability of the evidence base. Nonetheless, some limitations persist. For instance, despite overall quality ratings being high, several studies lacked longitudinal designs, limiting causal inference. This echoes concerns previously raised by Radicic and Petković (2023) regarding the short-term orientation of AI impact studies. Moreover, few studies in the meta-analysis provided cost-benefit analyses or explored the organizational learning curve associated with AI adoption. As emphasized by Zhao et al. (2023) the long-term return on AI investments depends on sustained data governance and continuous model updating. Future research should also examine how AI interacts with other emerging technologies—such as blockchain or IoT—to create synergistic effects on decision agility and forecasting precision. Despite these gaps, the current findings present compelling evidence that AI-based systems substantially improve the speed, accuracy, and flexibility of SME decision-making, especially when supported by appropriate organizational and technical infrastructures.

CONCLUSION

This meta-analysis demonstrates compelling evidence that artificial intelligence (AI)-driven decision support systems significantly enhance forecasting accuracy, strategic agility, and financial decision-making outcomes within small and medium-sized enterprises (SMEs). Synthesizing results from 67 empirical studies, the findings confirm that AI adoption yields consistent and statistically significant improvements in operational efficiency, budget control, demand forecasting, and scenario planning. The aggregated effect sizes reflect not only the technical superiority of machine learning and hybrid intelligence models but also the strategic benefits of integrating real-time analytics into everyday business decisions. Hybrid models, in particular, stood out as the most effective configurations, validating the complementary roles of algorithmic intelligence and human judgment. The effectiveness of AI interventions was shown to be context-sensitive, with higher gains observed in sectors such as manufacturing and retail, and in SMEs with more advanced digital infrastructure. Geographic disparities in AI effectiveness further highlighted the importance of digital maturity and institutional readiness in realizing the full value of AI technologies. Despite these advances, the findings also underscore the critical role of organizational culture, leadership commitment, and data governance in determining the success of AI deployment. AI tools are most impactful when integrated into decision-making frameworks that are agile, decentralized, and data-literate. The results reinforce the importance of treating AI not merely as a technical upgrade but as a transformational enabler that requires supportive ecosystems, including skilled personnel, robust IT infrastructure, and adaptive business models.

RECOMMENDATION

To fully realize the benefits of AI-driven decision support systems, SMEs should prioritize the strategic integration of these tools into core business functions rather than treating them as peripheral technologies. AI must be embedded in workflows such as cash flow management, dynamic budgeting, inventory planning, and customer segmentation, ensuring that predictive insights directly influence tactical and strategic choices. Managers and decision-makers should be encouraged to use AI outputs in real time, supported by well-designed dashboards, automated alerts, and scenario-based simulations. To facilitate this, organizations must invest in upskilling their workforce, focusing on data literacy, interpretation of machine learning outputs, and integration of AI into financial and operational planning. Business leaders should also select AI tools that are tailored to their specific sector and data environment, favoring hybrid models that combine machine learning capabilities with human-in-the-loop decision oversight. Vendor selection should emphasize modularity, transparency, and explainability, especially for SMEs in regulated sectors. Furthermore, SMEs are encouraged to utilize cloud-based analytics platforms that lower entry barriers through affordability, scalability, and ease of use. By aligning AI adoption with business strategy and ensuring that forecasts and recommendations feed directly into performance monitoring systems, SMEs can enhance decision-making agility, improve resource utilization, and strengthen long-term resilience. Given the disparity in AI benefits across regions and firm sizes, policy-makers and industry associations must play an active role in supporting SME readiness for AI adoption. Governments should implement targeted programs that subsidize AI tool implementation, especially for micro and small enterprises operating in resource-constrained environments. This includes offering tax incentives, digital transformation grants, and low-interest financing schemes to offset upfront costs associated with AI deployment. In parallel, investments in national digital infrastructure—such as cloud service accessibility, secure broadband connectivity, and data centers—are essential to enabling real-time, AI-powered decision-making across geographic regions. Training and advisory services should be expanded through chambers of commerce, innovation hubs, and academic institutions to improve SME capacity in data governance, cybersecurity, and algorithmic accountability. Regulatory frameworks should also evolve to promote transparency and fairness in AI applications, particularly in areas like credit scoring, pricing algorithms, and predictive employment analytics. Industry-wide benchmarking tools and AI-readiness assessment frameworks can help SMEs evaluate their maturity and chart incremental adoption pathways. Finally, fostering collaborative ecosystems—where SMEs, FinTech firms, AI vendors, and research institutions co-create sector-specific solutions—will enhance innovation diffusion and reduce redundancy in development efforts. These systemic interventions are vital to ensuring that AI-driven decision support becomes a sustainable, inclusive engine of productivity and competitiveness for SMEs globally.

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