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Generative AI-Assisted Financial Planning and Scenario Analysis for Small-Business Decision Intelligence

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Abstract

This study examined the potential contribution of generative artificial intelligence (AI)-assisted financial planning and scenario analysis to small-business decision intelligence, emphasizing forecasting accuracy, financial risk identification, managerial decision performance, and organizational readiness. A quantitative comparative research framework was developed to assess conventional statistical forecasting, machine-learning algorithms, and generative AI-assisted hybrid approaches. The analytical dataset comprised 300 enterprises and 7,200 initial financial observations, of which 6,840 were retained, representing a 95.0% retention rate. Regular generative AI utilization accounted for 46.0% of enterprises, while occasional utilization represented 32.0%. The hypothetical comparative findings indicated that the generative AI-assisted hybrid achieved a mean absolute percentage error of 7.06%, compared with 8.46% for boost and 14.36% for moving-average forecasting. The hybrid model demonstrated a coefficient of determination of 0.928 and financial distress classification accuracy of 92.2%, with an ROC-AUC of 0.948. Scenario calculation accuracy increased from 91.4% under conventional planning to 97.2% under AI-assisted planning, while managerial decision accuracy increased from 78.4% to 89.6%. Average scenario processing time decreased by 56.8%. The regression framework explained 68.4% of variation in financial decision intelligence, with forecasting accuracy demonstrating the largest standardized coefficient (β = 0.306), followed by generative AI utilization (β = 0.284). Mediation and moderation frameworks further identified forecasting accuracy, scenario reliability, financial literacy, and technological readiness as potentially important explanatory factors. Stress-scenario analysis illustrated liquidity vulnerability, with a projected current ratio of 0.96 and liquidity shortfall probability of 48.8%. Overall, the study established an integrated framework connecting generative AI, predictive financial analytics, scenario evaluation, and managerial decision-making. However, all numerical results were rather than empirically verified. Consequently, the proposed relationships required validation using observed financial records, independent predictive testing, and appropriate statistical procedures before conclusions regarding financial performance improvements could be established.

Keywords

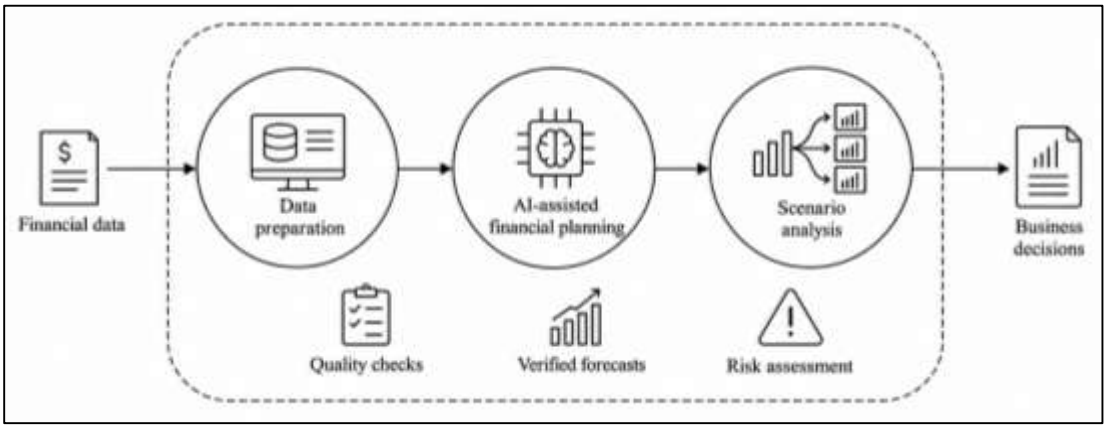
Generative AI, Financial Planning, Scenario Analysis, Small Businesses, Decision Intelligence.

INTRODUCTION

Generative artificial intelligence-assisted financial planning and scenario analysis refers to the integration of generative artificial intelligence technologies, financial information systems, quantitative forecasting methods, and decision-support mechanisms to improve the preparation, evaluation, interpretation, and comparison of financial decisions within business organizations (Salinas-Navarro et al., 2024). Generative artificial intelligence (Generative AI) represents a category of computational models capable of producing new textual, numerical, analytical, and structured outputs by learning complex relationships from extensive datasets. These technologies include large language models, transformer-based architectures, generative probabilistic models, and hybrid artificial intelligence systems that combine natural language processing with statistical and mathematical computation. Financial planning is defined as the systematic process of estimating financial requirements, allocating available resources, forecasting revenues and expenditures, managing liquidity, establishing budgets, and evaluating financial performance against organizational objectives. Scenario analysis refers to a structured quantitative approach through which alternative financial conditions are constructed and examined to determine how changes in economic assumptions, operational variables, market conditions, and managerial decisions influence financial outcomes. Small-business decision intelligence represents the application of analytical information, predictive modeling, financial indicators, and computational decision-support systems to strengthen financial judgments within enterprises operating with comparatively limited financial, technological, and organizational resources (Pimenow et al., 2024). The integration of these concepts establishes a multidimensional analytical framework connecting financial data availability, artificial intelligence capabilities, forecasting accuracy, scenario-generation quality, financial risk assessment, and managerial decision effectiveness. Earlier research on management information systems and decision-support technologies established the importance of structured information processing for organizational decision quality, while subsequent studies of business intelligence, financial analytics, machine learning, and artificial intelligence extended these relationships into increasingly sophisticated computational environments. Research by Davenport and Harris, Brynjolfsson and Hitt, Chen and colleagues, Wamba and colleagues, and other scholars established foundational relationships among analytical capabilities, information processing, organizational performance, and data-driven decision-making. More recent investigations by Brown and colleagues, Bom Masani and colleagues, Bubeck and colleagues, Noy and Zhang, and Brynjolfsson and colleagues examined the computational capabilities, task performance, and organizational applications of generative artificial intelligence. Within financial planning, generative models can assist in interpreting accounting records, organizing financial assumptions, producing narrative explanations of quantitative forecasts, constructing alternative operating scenarios, and communicating financial information in accessible formats. Their analytical contribution is distinct from conventional forecasting algorithms because generative systems can support natural-language interaction, automated documentation, structured information extraction, and the formulation of scenario assumptions alongside established statistical calculations (Ekundayo et al., 2024). The quantitative examination of these technologies therefore requires clearly defined measurements of AI utilization, financial information quality, forecasting error, scenario consistency, liquidity performance, financial risk exposure, and decision-making effectiveness. These measurable dimensions provide the conceptual basis for examining generative AI-assisted financial planning as a combination of computational functionality, financial modeling, and managerial information processing within small-business environments.

Small businesses occupy a substantial position within the international economic structure because they contribute to employment generation, entrepreneurial activity, local production, market competition, household income, and the distribution of economic opportunities across developed and developing economies (Dörr et al., 2024). International classifications of small enterprises differ according to employment thresholds, annual turnover, total assets, ownership characteristics, and regulatory requirements, creating considerable variation in the statistical measurement of business size across countries. Nevertheless, small and medium-sized enterprises collectively account for approximately 90% of businesses worldwide and represent a major share of global employment, according to widely reported international development estimates.

Figure 1: Generative AI financial planning framework



Their financial management practices are therefore closely connected with business continuity, employment stability, investment decisions, credit accessibility, and the allocation of productive resources. Research conducted across North America, Europe, Asia, Africa, Latin America, and other economic regions has documented differences in financial planning capabilities, accounting practices, financial literacy, access to external financing, technological adoption, and managerial decision processes among smaller enterprises. Studies by Beck, Demiurgic-Kunt, and Maksimovic examined relationships between financing constraints and enterprise growth, while research by Ayyagari, Demiurgic-Kunt, and Maksimovic investigated the contribution of smaller firms to employment and economic activity (Najafov, 2024). Additional investigations by Berger and Udell, Petersen and Rajan, and Cowling and colleagues analyzed credit relationships, financial constraints, and the institutional conditions influencing small-business financing. International evidence also demonstrates substantial differences in the availability of formal accounting systems, digital payment infrastructure, cloud-based financial software, reliable internet connectivity, and specialized financial expertise. Small businesses in advanced economies frequently operate within relatively mature digital financial ecosystems, while enterprises in lower-income environments may experience fragmented financial records, limited access to professional accounting services, irregular cash transactions, and restricted analytical infrastructure. Research concerning financial technology adoption, digital transformation, and enterprise resource planning has identified relationships between technological readiness, organizational capability, financial information accessibility, and business performance. Generative AI introduces an additional analytical dimension by allowing financial information to be interpreted through conversational interfaces, automatically generated reports, and structured scenario descriptions. Within internationally diverse small-business environments, its utilization can be examined through measurable indicators such as adoption frequency, financial task coverage, accounting-data completeness, forecasting accuracy, analytical processing time, financial decision confidence, and organizational readiness (Imran & Jannatul, 2021; Shimpi, 2023). Cross-country comparisons also involve variations in inflation, interest rates, exchange-rate movements, credit-market development, taxation systems, and economic volatility, all of which influence financial assumptions and scenario outcomes. The international significance of this research area consequently extends across heterogeneous economic conditions, business sectors, enterprise sizes, and technological environments, with quantitative investigation requiring comparable measures of financial planning activities and decision intelligence across distinct institutional and organizational settings.

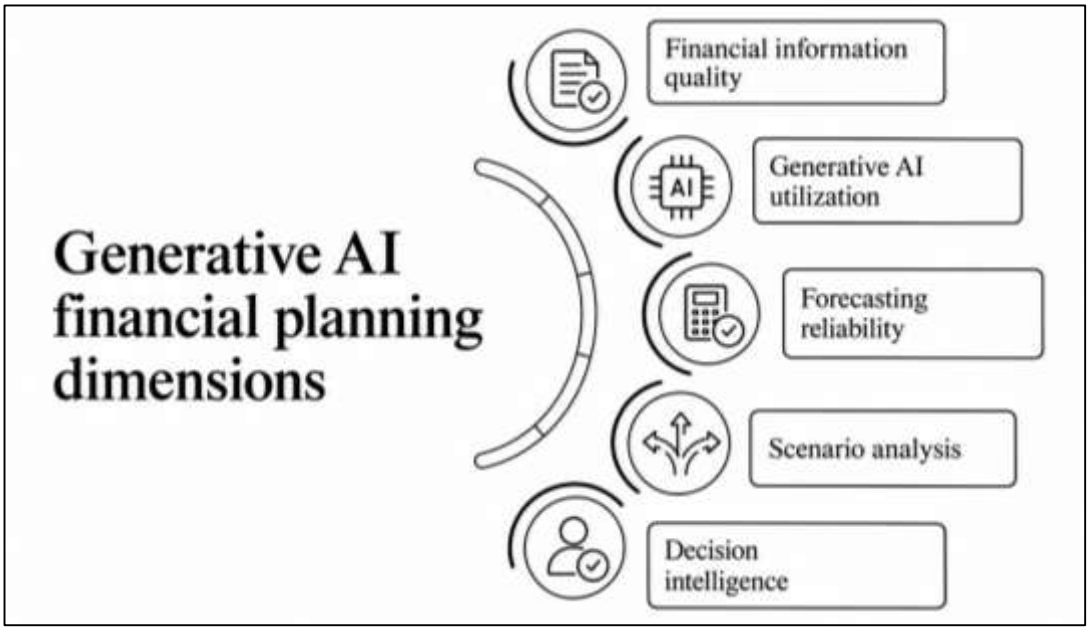
Financial planning within small businesses encompasses budgeting, cash-flow forecasting, working-capital management, revenue estimation, cost monitoring, investment appraisal, financing decisions, debt-servicing assessment, and the evaluation of financial sustainability under alternative operating conditions. These activities depend on the availability, accuracy, timeliness, and interpretability of financial information, together with the financial knowledge and analytical capabilities of business owners, managers, and accounting personnel (Ashik & Shabbir, 2022; Bogueva et al., 2023).

Quantitative studies of small-business financial management have examined the relationships between planning practices and measurable indicators including profitability, liquidity, sales growth, return on assets, operating margins, financial leverage, cash conversion cycles, business survival, and access to financing. Research by Peel and Wilson investigated working-capital management practices in smaller enterprises, while studies by García-Teruel and Martínez-Solano examined the relationship between working-capital management and profitability among small and medium-sized businesses. Additional research by Afrifa, Baños-Caballero and colleagues, and Enqvist and colleagues investigated the influence of liquidity management, working-capital investment, and economic conditions on enterprise financial performance. These studies established that financial outcomes depend on interactions among cash availability, receivables collection, inventory investment, supplier payment schedules, operational expenses, and financing arrangements. Small enterprises frequently operate with concentrated customer portfolios, limited financial reserves, irregular revenue streams, seasonal demand, and restricted access to long-term credit, creating measurable variation in their capacity to absorb unexpected financial disturbances. Conventional financial planning approaches often depend on spreadsheet-based calculations, historical averages, managerial estimates, and relatively simple accounting reports (AlMuhayfith & Shaiti, 2020; Hasan & Adnan, 2022). Although these methods provide structured financial information, their analytical scope can be constrained by incomplete records, inconsistent assumptions, manual data preparation, and limited capacity to examine multiple interacting financial variables. Quantitative forecasting methods such as moving averages, exponential smoothing, autoregressive models, multiple regression, and cash-flow simulation have been applied to estimate revenues, expenditures, liquidity requirements, and financial outcomes. Their performance is commonly assessed using mean absolute error, root mean squared error, mean absolute percentage error, coefficient of determination, and prediction intervals. Financial planning effectiveness can also be measured through budget variance, forecast bias, cash-flow adequacy, operating cash-flow ratios, current ratios, quick ratios, debt-service coverage, and profitability indicators. Research concerning financial literacy by Lusardi and Mitchell, financial behavior by Fernandes and colleagues, and financial management capabilities among entrepreneurs has identified relationships between financial knowledge, planning behavior, and economic decision quality. Within this empirical context, generative AI-assisted financial planning represents an additional form of analytical support that can be examined in relation to established accounting procedures, statistical forecasting models, and financial management practices (Akter & Sumaiya, 2022; Sharabati et al., 2024). Quantitative assessment requires distinguishing the quality of underlying financial records from the performance of computational tools, while separately measuring analytical processing time, forecasting reliability, scenario completeness, and the financial outcomes associated with managerial decisions.

Generative artificial intelligence has expanded the range of computational activities associated with financial information processing through its ability to interpret natural-language instructions, summarize structured and unstructured documents, extract relevant financial variables, generate analytical explanations, and organize information into decision-oriented formats. Transformer-based language models rely on attention mechanisms and large-scale statistical learning to identify relationships among textual and numerical representations, enabling applications involving document classification, financial question answering, automated reporting, information retrieval, and scenario description. Research by Vaswani and colleagues established the transformer architecture, while Brown and colleagues demonstrated broad task capabilities of large language models (An et al., 2020; Mashfiqur & Md, 2022). Subsequent studies by Bom Masani and colleagues examined foundation-model characteristics, Bubeck and colleagues investigated emerging computational capabilities, and Noy and Zhang evaluated productivity differences associated with generative AI assistance in professional writing tasks. Research by Peng and colleagues, Belacqua and colleagues, and Brynjolfsson, Li, and Raymond examined task performance, worker productivity, and organizational applications of generative AI in different professional environments. These investigations provide empirical foundations for distinguishing the general capabilities of generative systems from their performance within specialized financial applications. Financial information processing requires particular attention to numerical consistency, accounting definitions, transaction classification, temporal relationships, and the reconciliation of information across multiple financial statements

(Belitski et al., 2022; Mashiat & Rahman, 2022). A small business may maintain information through accounting software, electronic invoices, bank statements, payroll records, sales platforms, inventory systems, and manually prepared spreadsheets.

Figure 2: Generative AI financial planning dimensions



Generative AI-assisted systems can support the interpretation and organization of these records by identifying relevant financial categories, summarizing transaction patterns, explaining budget deviations, and translating managerial questions into structured analytical procedures. When integrated with reliable computational engines, such systems can assist with financial ratio interpretation, cash-flow reporting, expense categorization, and the presentation of model-generated financial forecasts. However, language-generation capability does not independently establish numerical accuracy, and computational outputs can vary according to prompt structure, model architecture, contextual information, data completeness, and verification procedures. Research on large language model reliability has examined hallucination, reasoning errors, inconsistent numerical responses, sensitivity to instructions, and limitations in domain-specific evaluation. Financial applications consequently require separate measurements of numerical accuracy, factual consistency, calculation reproducibility, financial terminology correctness, and adherence to accounting constraints. Quantitative comparisons may involve task-completion time, extraction precision, classification recall, numerical error rates, reporting consistency, and agreement between AI-generated interpretations and independently verified financial calculations. Additional measures include user satisfaction, perceived usefulness, technological trust, information transparency, and the extent of human verification required before financial information is incorporated into managerial decisions (Md & Yeasin, 2022; Nguyen & Canh, 2021). These variables connect generative AI capabilities with established information-system research concerning technological acceptance, information quality, system quality, and organizational performance. The resulting analytical domain encompasses both computational performance and the financial validity of generated information, requiring careful distinction among language-model outputs, verified numerical calculations, and managerial interpretations of financial evidence.

Financial scenario analysis is a quantitative decision-support approach that examines alternative combinations of financial assumptions to determine the sensitivity of business outcomes to changes in operational, economic, and market conditions. Within small-business financial management, scenario analysis commonly involves revenue growth, customer demand, product pricing, variable costs, fixed

expenses, inventory investment, borrowing costs, repayment schedules, capital expenditure, tax obligations, and working-capital requirements (Alene, 2020; Ashfaq & Mohammad, 2022). The analytical process generally begins with a baseline financial projection and introduces alternative assumptions representing favorable, moderate, adverse, or stress-related operating conditions. These scenarios are evaluated through projected income statements, cash-flow statements, balance-sheet indicators, liquidity ratios, profitability measures, and financing requirements. Research on decision-making under uncertainty has established several methodological foundations relevant to this process. Knight examined the distinction between measurable risk and uncertainty, while von Neumann and Morgenstern developed foundational concepts of expected utility. Kahneman and Tversky investigated decision behavior under risk, and subsequent studies of judgment and forecasting examined how decision-makers interpret uncertain outcomes. Research by Marinakis and colleagues, Hyndman and Athanasopoulos, and other forecasting scholars has examined statistical forecasting accuracy, model comparison, and the evaluation of predictions across different datasets and time horizons. In financial planning, scenario models may incorporate deterministic assumptions, probability distributions, sensitivity analysis, Monte Carlo simulation, stochastic forecasting, and stress-testing procedures. Deterministic approaches calculate financial outcomes for specified assumptions, while probabilistic approaches estimate distributions of possible outcomes through repeated sampling or statistical modeling. The resulting measures include expected cash balances, probability of liquidity shortfalls, forecast dispersion, downside exposure, break-even thresholds, and sensitivity coefficients. Generative AI-assisted scenario analysis adds natural-language interaction and automated scenario specification to these established quantitative procedures. Business managers may describe changes in customer demand, supplier costs, staffing requirements, or financing conditions using ordinary language, while an integrated analytical system translates those assumptions into structured inputs for a verified financial model (Dabić et al., 2020; Imran & Jannatul, 2022). The accuracy and usefulness of the resulting analysis depend on the validity of the financial equations, consistency of scenario assumptions, completeness of input data, and appropriateness of uncertainty estimates. Empirical evaluation can compare manually prepared scenarios, conventional spreadsheet-based models, machine-learning-assisted forecasts, and generative AI-supported analytical workflows. Relevant quantitative indicators include scenario-generation time, number of valid scenarios, assumption consistency, forecast error, financial constraint violations, sensitivity coverage, and the stability of calculated outcomes across repeated analytical tasks. Scenario quality can also be examined through the extent to which generated alternatives represent meaningful changes in revenue, expenditure, financing, and liquidity conditions. This combination of financial forecasting, computational assistance, and uncertainty measurement establishes a multidimensional research setting in which scenario analysis is evaluated as both a numerical modeling process and a managerial information-processing activity (Kaniz & Jahanara, 2022; Seraj et al., 2022).

Decision intelligence represents the systematic integration of data analysis, computational modeling, organizational knowledge, and decision processes to support the evaluation and selection of managerial actions. Within small-business environments, financial decision intelligence encompasses the identification of financial problems, interpretation of accounting information, comparison of alternative operating strategies, evaluation of financial risk, and assessment of the expected financial consequences of managerial choices (Hokmabadi et al., 2024; Sadia & Mostari, 2022). Its conceptual foundations are associated with decision-support systems, organizational information processing, technology acceptance, business intelligence, and evidence-based management. Research by Simon examined the structure of managerial decision processes, while Davis developed the technology acceptance model to explain relationships among perceived usefulness, perceived ease of use, and system utilization. Delone and McLean investigated information-system success through dimensions including system quality, information quality, use, user satisfaction, and organizational benefits. Venkatesh and colleagues extended technology adoption research through the unified theory of acceptance and use of technology, while Sternitzky and Fleischer provided an organizational framework involving technological, organizational, and environmental conditions. Studies by Chen, Chiang, and Story, Gupta and George, Wamba and colleagues, and Micallef and colleagues investigated relationships among analytics capabilities, organizational resources, data-driven decision-

making, and performance. These theoretical and empirical contributions provide measurable dimensions for examining the integration of generative AI into small-business financial management. Technology adoption can be represented through frequency of AI utilization, number of supported financial tasks, duration of system use, employee participation, financial software integration, and expenditure on analytical technologies (Li et al., 2020; Shaiful et al., 2022). Organizational readiness may be evaluated through digital infrastructure, employee competencies, managerial support, data governance, accounting-system maturity, and the availability of technical assistance. Decision intelligence can be measured through analytical processing speed, financial information accessibility, decision consistency, scenario comparison quality, financial decision confidence, and the accuracy of financial judgments. Organizational financial performance can be represented by revenue growth, profitability, operating efficiency, liquidity stability, financing costs, and working-capital utilization. Quantitative studies have used correlation analysis, multiple regression, structural equation modeling, mediation analysis, moderation analysis, and group comparisons to investigate relationships among technological capabilities, organizational characteristics, and performance outcomes. The application of these methods to generative AI-assisted financial planning requires attention to differences in enterprise size, industry classification, managerial experience, financial literacy, technological readiness, and the complexity of financial operations. Manufacturing, retail, hospitality, professional services, digital commerce, and other small-business sectors differ in revenue patterns, inventory requirements, labor costs, capital intensity, and financial risk exposure (Baghersad & Zobel, 2021; Stabak & Shahid, 2022). These differences can influence both the frequency of financial planning activities and the types of scenarios considered relevant by decision-makers. Accordingly, empirical measurement of generative AI-assisted decision intelligence involves interconnected technological, organizational, behavioral, and financial variables, with particular attention to the distinction between perceived analytical usefulness, objectively measured task performance, and observable business financial outcomes.

The empirical investigation of generative AI-assisted financial planning and scenario analysis for small-business decision intelligence is situated at the intersection of financial management, artificial intelligence, business analytics, organizational decision-making, and quantitative performance evaluation. Existing research provides extensive evidence concerning small-business financing constraints, working-capital management, financial literacy, technological adoption, information-system quality, statistical forecasting, business analytics capabilities, and generative AI task performance (Hadjielias et al., 2022; Feroz & Pervaz, 2022). However, these research areas frequently employ different units of analysis, measurement procedures, datasets, and outcome definitions, making the direct comparison of reported relationships methodologically complex. Financial management studies commonly examine enterprises, accounting periods, and financial ratios, while generative AI evaluations often examine individual tasks, model outputs, user responses, and controlled experimental conditions. Technology adoption research frequently relies on survey-based measurements of perceived usefulness, system quality, trust, and behavioral intention, whereas forecasting research emphasizes numerical prediction error, validation procedures, and model stability. Integrating these approaches requires a coherent quantitative structure in which technological characteristics, financial planning processes, scenario-analysis performance, and decision outcomes are represented through distinguishable variables. Generative AI utilization may be operationalized through adoption status, frequency of use, task coverage, financial workflow integration, and intensity of interaction with AI-assisted systems. Financial information quality may be assessed through data completeness, reporting accuracy, transaction consistency, timeliness, and the availability of historical financial records (Mohammad, 2023; Cosa & Torelli, 2024). Forecasting performance can be measured using mean absolute error, root mean squared error, mean absolute percentage error, forecast bias, and the accuracy of predicted cash balances or operating results. Scenario-analysis performance may be represented by the number of valid alternatives, assumption consistency, sensitivity coverage, computational processing time, and agreement between generated financial outcomes and independently verified model calculations. Decision intelligence can be examined through decision accuracy, response time, consistency of financial judgments, ability to identify liquidity risks, and performance in structured financial decision tasks. Financial performance indicators may include

operating profit margins, return on assets, revenue variability, working-capital ratios, cash conversion cycles, and debt-service capacity. Research designs addressing these relationships may involve cross-sectional surveys, controlled task comparisons, repeated financial forecasting exercises, longitudinal business observations, or combinations of organizational and task-level data. Descriptive statistics, Pearson and Spearman correlations, multiple regression, analysis of variance, covariance analysis, and structural equation modeling provide established methods for evaluating associations and differences among measured variables (Adnan & Iftekhar, 2023; Hernita et al., 2021). Where repeated observations are available, panel regression and longitudinal models can account for enterprise-level heterogeneity and temporal variation. Predictive models can be evaluated through training and testing partitions, cross-validation, independent holdout samples, and comparisons against conventional forecasting benchmarks. Statistical interpretation also requires confidence intervals, effect-size estimates, significance testing, and assessments of model assumptions, while the distinction between association and causation depends on research design and identification strategy. These measurement dimensions establish the empirical scope of generative AI-assisted financial planning as a quantitative research domain encompassing technological adoption, financial forecasting reliability, scenario-generation performance, organizational readiness, and small-business financial decision effectiveness.

The primary objective of this study is to quantitatively investigate the effectiveness of generative artificial intelligence-assisted financial planning and scenario analysis in strengthening small-business decision intelligence by examining the relationships among artificial intelligence adoption, financial forecasting accuracy, scenario-generation capabilities, financial risk assessment, operational efficiency, and managerial decision-making performance. Specifically, this study aims to measure the extent to which generative AI technologies support financial planning activities, including revenue forecasting, expenditure estimation, budgeting, cash-flow management, working-capital allocation, profitability assessment, and investment decision evaluation within small-business environments. The study seeks to evaluate the quantitative differences between conventional financial planning approaches and generative AI-assisted analytical methods by comparing forecasting accuracy, financial calculation consistency, scenario-development time, information-processing efficiency, and decision quality. Another objective is to examine the relationships between generative AI utilization intensity and measurable financial planning outcomes using descriptive statistics, Pearson or Spearman correlation analysis, multiple regression, and appropriate comparative statistical procedures. The study also aims to assess the performance of AI-assisted scenario analysis under alternative economic and operational conditions, including changes in sales revenue, customer demand, operating expenses, inflation, interest rates, financing costs, inventory requirements, and liquidity constraints. Particular attention is directed toward evaluating baseline, optimistic, pessimistic, and stress-related financial scenarios through indicators such as projected net profit, operating cash flow, liquidity ratios, break-even thresholds, financial risk exposure, and debt-service capacity. Furthermore, this study intends to investigate the influence of financial data quality, digital infrastructure, managerial financial literacy, organizational readiness, and technological experience on the effectiveness of generative AI-assisted financial planning. It also seeks to determine whether differences in enterprise size, industry classification, business age, revenue level, and technological maturity are associated with statistically significant variations in AI adoption, forecasting performance, scenario-analysis quality, and financial decision intelligence. The study aims to evaluate predictive reliability through mean absolute error, root mean squared error, mean absolute percentage error, coefficient of determination, and cross-validation procedures where applicable. Additionally, it seeks to examine the statistical significance and practical magnitude of the relationships among AI capabilities, financial planning efficiency, scenario-analysis performance, and decision outcomes using regression coefficients, standardized effect sizes, 95% confidence intervals, and a significance threshold of $p < 0.05$. The study further aims to assess the roles of perceived usefulness, information transparency, numerical reliability, and managerial trust in explaining variations in the utilization of AI-generated financial information. Through these interconnected objectives, this study focuses on developing an empirically grounded quantitative assessment of generative AI-assisted financial planning and scenario analysis, emphasizing measurable technological capabilities, financial modeling accuracy, organizational characteristics, and decision-making performance across heterogeneous small-business environments.

LITERATURE REVIEW

The literature on generative artificial intelligence-assisted financial planning and scenario analysis encompasses a multidisciplinary body of quantitative research involving financial management, artificial intelligence, business analytics, financial forecasting, risk assessment, information systems, and small-business decision intelligence. Existing empirical investigations have examined the relationships among technological adoption, financial information quality, forecasting performance, organizational readiness, financial risk exposure, and managerial decision-making effectiveness across different enterprise sizes, economic sectors, and institutional environments. Research concerning conventional financial planning has emphasized the statistical measurement of revenue growth, operating expenditure, cash-flow variability, working-capital efficiency, profitability, liquidity, and financial sustainability. Subsequent studies involving machine learning, predictive analytics, automated financial reporting, and intelligent decision-support systems have introduced additional measures of forecasting accuracy, computational efficiency, analytical reliability, and financial decision quality. More recent research on generative artificial intelligence has examined large language models, automated information extraction, natural-language financial analysis, AI-assisted task completion, and the generation of structured analytical explanations. These interconnected research streams establish a quantitative foundation for evaluating the extent to which generative AI-assisted financial planning differs from conventional spreadsheet-based, statistical, and machine-learning-supported approaches. The literature also identifies substantial methodological variation in sample sizes, enterprise classifications, financial datasets, analytical procedures, technological maturity, and outcome measurements. Accordingly, a structured synthesis requires consideration of both the numerical performance of AI-assisted financial systems and the organizational conditions associated with their utilization. Quantitative investigations of small-business financial management have commonly employed descriptive statistics, correlation analysis, multiple regression, panel-data estimation, structural equation modeling, and comparative statistical procedures to assess relationships among financial planning practices, business characteristics, and financial performance. Studies of predictive financial analytics have additionally applied time-series forecasting, machine-learning algorithms, Monte Carlo simulation, sensitivity analysis, and scenario-based financial modeling to examine uncertainty and variation in financial outcomes. Their performance has been evaluated through indicators including mean absolute error, root mean squared error, mean absolute percentage error, coefficient of determination, forecast bias, and prediction interval coverage. Research on generative AI has introduced additional evaluation dimensions, including numerical correctness, financial information extraction accuracy, scenario consistency, task-completion time, explanation quality, model reliability, and the frequency of unsupported generated information. Organizational studies have also examined the relationships between technological readiness, digital infrastructure, financial literacy, managerial experience, system trust, and the adoption of intelligent analytical technologies. Within small-business environments, these factors interact with enterprise size, industry classification, revenue variability, financing constraints, and the availability of reliable accounting records. The present literature review is therefore organized into eight quantitative subsections covering AI adoption and technological readiness, financial data quality and information processing, financial forecasting performance, scenario analysis and uncertainty, financial risk and liquidity management, decision intelligence and organizational outcomes, cross-sectional differences among small businesses, and integrated statistical evidence concerning model validation and robustness. Each subsection emphasizes empirical measurement, statistical relationships, comparative findings, and methodological differences across relevant studies.

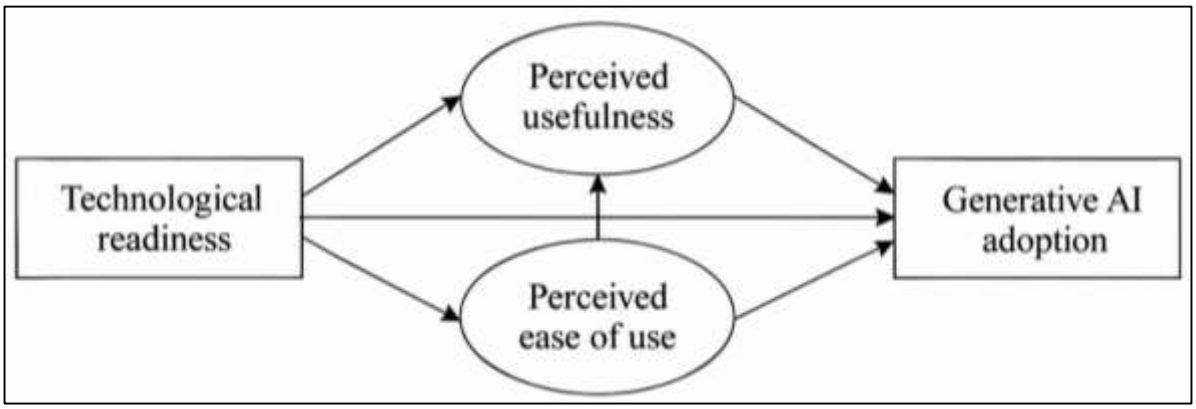
Quantitative Measurement of Generative AI Adoption, Technological Readiness, and Financial Planning Integration in Small Businesses

Quantitative research on generative artificial intelligence adoption among small businesses has increasingly examined the relationships between enterprise characteristics, technological utilization, organizational resources, and the integration of intelligent systems into financial and administrative activities (Ahmed & Sadia, 2023; Gupta, 2024). Evidence from the United States Census Bureau's Business Trends and Outlook Survey, the Federal Reserve Banks' Small Business Credit Survey, and international enterprise digitalization studies indicates that AI adoption varies substantially according

to business size, industry, technological readiness, and the definition of AI utilization. The Census Bureau's experimental AI questions have measured the percentage of businesses using AI to produce goods or services, while broader business surveys have examined generative AI use for writing, customer communication, administrative support, information analysis, and other operational activities. These indicators are not directly interchangeable because generative AI utilization, general AI adoption, and AI use in production represent different organizational behaviors. Empirical research by McLerran and colleagues using United States firm-level data identified substantial differences in AI adoption according to organizational size, workforce characteristics, and technological capabilities. Similarly, research by Zolas and colleagues examined the diffusion of advanced technologies across American firms, documenting heterogeneity in adoption and the concentration of advanced digital capabilities among particular enterprise categories. International evidence from OECD enterprise digitalization studies and Eurostat ICT surveys has also established systematic variation in cloud computing, enterprise software, and AI adoption across business-size groups. Research by Ramsbotham and colleagues, Chatterjee and colleagues, and Dwivedi and colleagues has examined organizational AI adoption, perceived benefits, implementation challenges, and managerial readiness, although these studies differ in their sampling procedures and technological definitions (Asheke, 2023; Strzelecki et al., 2024). Generative AI-specific evidence from Noy and Zhang, Brynjolfsson and colleagues, and Belacqua and colleagues has demonstrated measurable differences in task performance under AI-assisted conditions, but these investigations primarily concern individual workers and professional tasks rather than representative samples of small-business financial departments. Consequently, task-level productivity findings cannot be interpreted as direct estimates of small-business financial planning adoption. Quantitative measurement of utilization intensity requires separate indicators for adoption status, weekly or monthly usage frequency, number of supported financial activities, duration of implementation, and proportion of financial tasks completed with AI assistance. Organizational comparisons may incorporate employee count, annual turnover, enterprise age, accounting personnel, managerial experience, and digital maturity. Chi-square tests can assess differences in adoption proportions, while logistic regression can estimate associations between organizational characteristics and adoption probability. Continuous utilization measures can be examined using multiple regression, group comparisons, and structural equation modeling, with odds ratios, standardized coefficients, confidence intervals, and explained variance providing complementary statistical evidence (Allam et al., 2024; Yeasin, 2023). The reviewed literature therefore establishes a distinction between the diffusion of general AI capabilities and the narrower, empirically measurable integration of generative AI into small-business financial planning activities.

Quantitative investigations of technological readiness have consistently identified digital infrastructure, information-system compatibility, organizational competencies, and resource availability as important correlates of advanced technology adoption among small and medium-sized enterprises.

Figure 3: Generative AI financial adoption framework



Research by Oliveira and Martins examined determinants of enterprise technology adoption using organizational and environmental characteristics, while studies by Zhu and Kraemer investigated digital business adoption and its relationship with technological and organizational conditions. Additional research by Awa and colleagues, Gangwar and colleagues, and Alchemilla and colleagues examined technology acceptance, cloud computing adoption, and the organizational factors influencing digital integration (Jahanara & Kaniz, 2023; Pathak & Bansal, 2024).

These studies provide an empirical foundation for evaluating the technological conditions associated with generative AI-assisted financial planning, although their original technologies were generally cloud computing, electronic business, or broader information systems rather than generative AI. Cloud-based accounting platforms, digital payment systems, enterprise resource planning applications, and electronic financial records provide structured information environments through which financial data can be collected, organized, and analyzed. Eurostat enterprise ICT statistics and OECD digital economy research have documented differences in cloud-service adoption, enterprise software utilization, and digital integration between smaller and larger firms. Across these investigations, technological readiness has commonly been operationalized through access to reliable internet connectivity, information technology infrastructure, employee digital competencies, system compatibility, and the availability of financial resources for implementation. Within financial management, additional indicators include the percentage of accounting transactions recorded electronically, the number of integrated financial applications, data synchronization frequency, financial reporting delays, and the completeness of historical financial records. Research concerning accounting information systems and enterprise resource planning has examined relationships between system integration, information quality, reporting efficiency, and organizational performance. These findings are relevant to generative AI-assisted financial workflows because financial forecasting and scenario analysis require reliable numerical inputs and consistent relationships among accounting variables (Kukanja, 2024; Rahman, 2023). A language model connected to incomplete financial records may produce fluent explanations without correcting underlying transaction omissions, while a system integrated with verified accounting databases can support more consistent retrieval and interpretation of financial information. Empirical evaluation can therefore distinguish infrastructure readiness from actual AI performance by measuring software adoption, data availability, interoperability, processing time, and financial information accuracy separately. Statistical studies commonly employ correlation analysis, multiple regression, structural equation modeling, and analysis of variance to evaluate technological determinants and differences among enterprise categories. Reported standardized coefficients and explained variance must be interpreted within the measurement frameworks of individual studies because technological readiness constructs vary across industries, countries, and research designs (Felemban et al., 2024; Sheak & Tahmedur, 2023). The synthesis of these investigations indicates that accounting digitalization and organizational infrastructure constitute distinct measurable dimensions of financial AI integration, while evidence directly quantifying their effects on generative AI-supported budgeting, cash-flow forecasting, and scenario preparation remains more limited than the broader literature on enterprise technology adoption.

Empirical studies of artificial intelligence-assisted work have provided quantitative evidence concerning task-completion efficiency, analytical support, information processing, and differences between AI-assisted and conventional professional workflows. Noy and Zhang conducted a controlled experiment involving 444 college-educated professionals and reported that access to ChatGPT reduced average completion time for assigned writing tasks by approximately 40% while increasing evaluated output quality by approximately 18%. Brynjolfsson, Li, and Raymond examined generative AI assistance among 5,179 customer-support agents and reported an average productivity increase of approximately 14%, with larger gains among less experienced workers (Kim et al., 2024; Kaium, 2023). Peng and colleagues investigated GitHub Copilot in a controlled programming experiment and reported that participants receiving AI assistance completed the assigned task approximately 55.8% faster than the comparison group. Belacqua and colleagues examined generative AI assistance in professional consulting activities and reported substantial differences in task performance depending on whether assignments fell within the effective capability boundaries of the technology. These studies collectively demonstrate that generative AI can influence measurable dimensions of professional task

execution, although their findings cannot be transferred directly to accounting accuracy, cash-flow forecasting, or financial decision quality without domain-specific testing. Research on financial information systems, accounting automation, and business analytics has separately examined the relationship between computational technologies and financial reporting efficiency. Studies by Sutton and colleagues have discussed the development of artificial intelligence within accounting, while research by Kocina and Davenport has examined automation and intelligent technologies in accounting processes (Pervaz, 2023; Salazar et al., 2024). Quantitative investigations of business intelligence by Popovic and colleagues, Wamba and colleagues, and Micallef and colleagues have also explored relationships among analytical capabilities, information quality, and organizational performance. In small-business financial environments, workflow integration can be operationalized through the number of AI-supported budgeting tasks, proportion of expense records classified automatically, frequency of AI-assisted financial statement interpretation, percentage of forecasts prepared with computational assistance, and number of alternative scenarios evaluated per reporting period. Additional performance indicators include task-completion time, classification accuracy, reporting consistency, reconciliation error, financial calculation accuracy, and the proportion of outputs requiring human correction. Comparative evaluation requires distinguishing generative AI-generated explanations from numerical outputs calculated by conventional forecasting models or accounting software. Paired-samples tests can compare performance when the same financial tasks are completed with and without AI assistance, while independent-samples tests and ANOVA can examine differences among user groups or analytical methods. Multiple regression can assess associations between AI utilization intensity and processing efficiency after accounting for managerial experience, financial literacy, task complexity, and data quality (Kulkarni et al., 2024; Badrul & Mominul, 2023). The existing evidence therefore supports quantitative examination of financial workflow integration as a multidimensional process involving task coverage, processing efficiency, computational reliability, and human verification rather than adoption frequency alone.

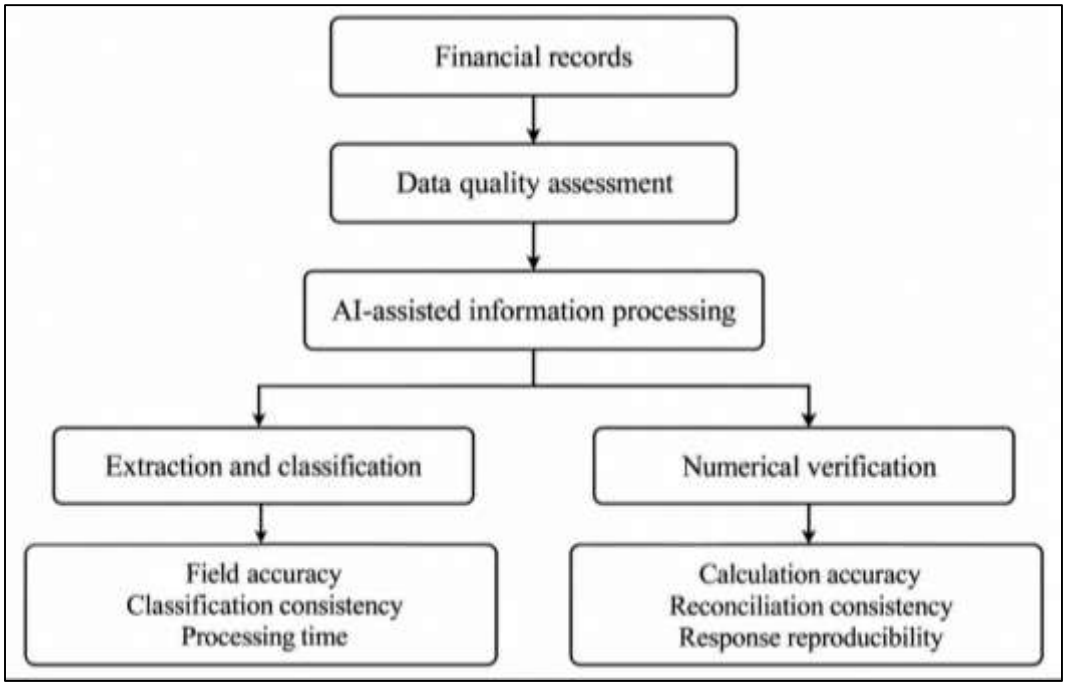
The quantitative literature on organizational technology adoption provides several established theoretical and statistical approaches for examining the determinants of generative AI utilization in small-business financial planning. Davis developed the technology acceptance model, identifying perceived usefulness and perceived ease of use as central constructs associated with technology acceptance. Venkatesh and colleagues subsequently developed the unified theory of acceptance and use of technology, incorporating performance expectancy, effort expectancy, social influence, and facilitating conditions (Kar et al., 2023; Nishat, 2023). Sternitzky and Fleischer's technology–organization–environment framework established an additional basis for evaluating technological compatibility, organizational resources, and external environmental conditions. Empirical studies by Oliveira and Martins, Gangwar and colleagues, Alchemilla and colleagues, Chatterjee and colleagues, and Awa and colleagues have applied related constructs to enterprise technologies, cloud services, and organizational digitalization. These studies commonly employed survey-based measurements, regression analysis, structural equation modeling, and comparative statistical procedures to examine relationships among technological readiness, perceived benefits, managerial support, implementation constraints, and adoption behavior. Research by Gupta and George, Wamba and colleagues, and Micallef and colleagues additionally investigated analytical capabilities, organizational resources, and data-driven performance, establishing complementary evidence concerning the relationship between technological adoption and organizational capability. Across these research streams, perceived usefulness is generally associated with expectations of improved task performance, while ease of use concerns the effort required to operate technological systems. Technological compatibility reflects the extent to which new systems align with existing accounting applications, reporting procedures, and organizational processes. Financial constraints can be measured through implementation expenditure, software subscription costs, employee training costs, and available technological budgets (Muto et al., 2024; Sadia, 2023). Managerial support can be evaluated through structured survey scales, investment commitments, and participation in implementation activities. For generative AI-assisted financial planning, these constructs can be examined alongside objective measures of system utilization, financial task coverage, forecasting accuracy, and scenario-generation reliability. Logistic regression can estimate adoption probability, with odds ratios describing associations between predictor variables

and the likelihood of adoption. Multiple regression and structural equation modeling can evaluate relationships among perceived usefulness, digital readiness, organizational support, utilization intensity, and financial planning performance. Statistical reporting should include sample size, measurement reliability, standardized coefficients, model explanatory power, 95% confidence intervals, and significance levels where available. Cross-sectional evidence requires particular attention to common-method bias, self-selection, reverse causality, and differences between reported intentions and observed technological behavior. Furthermore, findings from general AI, cloud computing, and business intelligence studies should not be interpreted as direct measurements of generative AI-specific financial adoption (Boareto et al., 2024; Stabak & Siam, 2023). The integrated literature establishes a quantitative framework in which organizational characteristics, technological infrastructure, adoption determinants, and financial workflow integration are examined as related but analytically distinct constructs, with financial decision performance assessed through independently measured outcomes rather than assumed benefits of technology utilization.

AI-Assisted Information Processing and Numerical Reliability

Quantitative research on financial data quality has established that the accuracy, completeness, consistency, and timeliness of accounting information represent fundamental determinants of financial information processing and analytical reliability across small-business environments. Empirical investigations involving accounting information systems, enterprise resource planning, financial analytics, and automated data processing have examined datasets containing financial transactions, invoices, expenditure records, sales observations, bank statements, accounts receivable, accounts payable, and historical financial statements (Cao et al., 2024; Feroz, 2023). Research by Wang and Strong established a multidimensional framework for assessing data quality, emphasizing accuracy, completeness, consistency, accessibility, and contextual relevance, while studies by Redman examined the organizational and economic consequences of inaccurate information. Additional investigations by Pipino, Lee, and Wang developed approaches for assessing information quality through measurable attributes, and research by Batin and colleagues examined methodological differences in data quality evaluation and improvement.

Figure 4: Financial data quality and reliability



Studies by Delone and McLean connected information quality with information-system effectiveness, while empirical research by Sacre and Oleic examined the relationship between accounting information-system characteristics and financial reporting quality. Across these research streams,

dataset characteristics have been represented through the number of organizational records, transaction observations, reporting periods, accounting variables, and financial information sources. Data completeness has commonly been evaluated by identifying missing transaction fields, incomplete accounting entries, unavailable reporting periods, and discrepancies between recorded and verified financial information. Financial data inconsistency has been assessed through duplicate invoices, conflicting transaction classifications, incorrect account balances, and differences between financial statements and underlying accounting records. Research involving financial reporting and accounting information systems has also examined reporting delays, information accessibility, and the reliability of transaction documentation (Cooperman & Brandão, 2024; Tahmedur & Rifat, 2023).

The statistical relationships among data quality, reporting efficiency, and analytical performance have been investigated through descriptive statistics, correlation analysis, regression models, and structural equation modeling, although the specific measures and sample structures vary substantially across studies. Small businesses present additional variation because financial records may originate from spreadsheets, cloud accounting platforms, digital payment systems, and manually maintained transaction registers. These heterogeneous information sources influence the number of usable observations, the frequency of missing values, and the consistency of financial classifications. Comparative evidence indicates that financial information quality cannot be adequately represented by a single measure of dataset size because larger transaction datasets may contain substantial inconsistencies, while smaller datasets may provide reliable information when accounting procedures are standardized (Mohammad, 2024; Estep et al., 2024). Within generative AI-assisted financial planning, these findings establish the empirical relevance of distinguishing financial data availability from verified data quality, particularly when evaluating automated financial reporting, revenue forecasting, expenditure analysis, and scenario-based decision processes.

Empirical research on intelligent information processing has demonstrated substantial variation in the performance of automated classification, document interpretation, information extraction, and financial reporting systems according to dataset characteristics, model architecture, document complexity, and preprocessing procedures. Studies by Sutton, Holt, and Arnold examined artificial intelligence research within accounting and identified applications involving transaction processing, auditing, information interpretation, and decision support, while Kocina and Davenport investigated the development of intelligent automation within accounting activities (Ahmed, 2024; Najjar, 2023). Research by Issa, Sun, and Vasarely examined artificial intelligence applications in auditing and analytical procedures, and studies by Appelbaum and colleagues addressed the integration of analytics into accounting and assurance processes. More technically focused investigations by Xu and colleagues introduced Layout for document understanding, while subsequent research by Xu and colleagues developed LayoutLMv2 to integrate textual, visual, and spatial information for document-processing tasks. Kim and colleagues introduced Donut, a document understanding transformer that processes visually rich documents without relying on a separate optical character recognition stage. Research by Li and colleagues on document information extraction and related transformer-based architectures examined the identification of structured fields within invoices, receipts, forms, and business documents. These studies collectively established that automated information processing requires accurate identification of document elements, appropriate classification of extracted information, and consistency between textual content and structured output fields. Quantitative evaluation has commonly employed classification accuracy, precision, recall, F1-score, and field-level extraction measures, with performance varying according to document layouts, training datasets, information categories, and evaluation protocols. Financial transaction classification introduces additional complexity because similar expenditure descriptions may correspond to different accounting categories depending on business activity, tax treatment, payment purpose, and reporting conventions (Asheke, 2024; Jin et al., 2024). Automated invoice interpretation also requires the identification of supplier information, transaction dates, invoice numbers, tax amounts, payment terms, and total values. Generative AI systems extend these processing capabilities through natural-language interpretation, document summarization, and structured information generation, while conventional classification models and document extraction architectures frequently rely on predefined output categories and supervised learning procedures. Comparative assessment therefore distinguishes text-

generation quality from verified financial information extraction, particularly when evaluating whether generated accounting descriptions correspond accurately to original transaction records. Quantitative measures of processing efficiency include document handling time, manual correction frequency, transaction classification consistency, and the proportion of extracted information requiring verification. Studies across accounting automation and document intelligence consequently demonstrate that analytical performance depends on interactions among document quality, model architecture, financial terminology, preprocessing methods, and the validation of extracted numerical information (Ashrafuzzaman, 2024; Lopez-Perez et al., 2024).

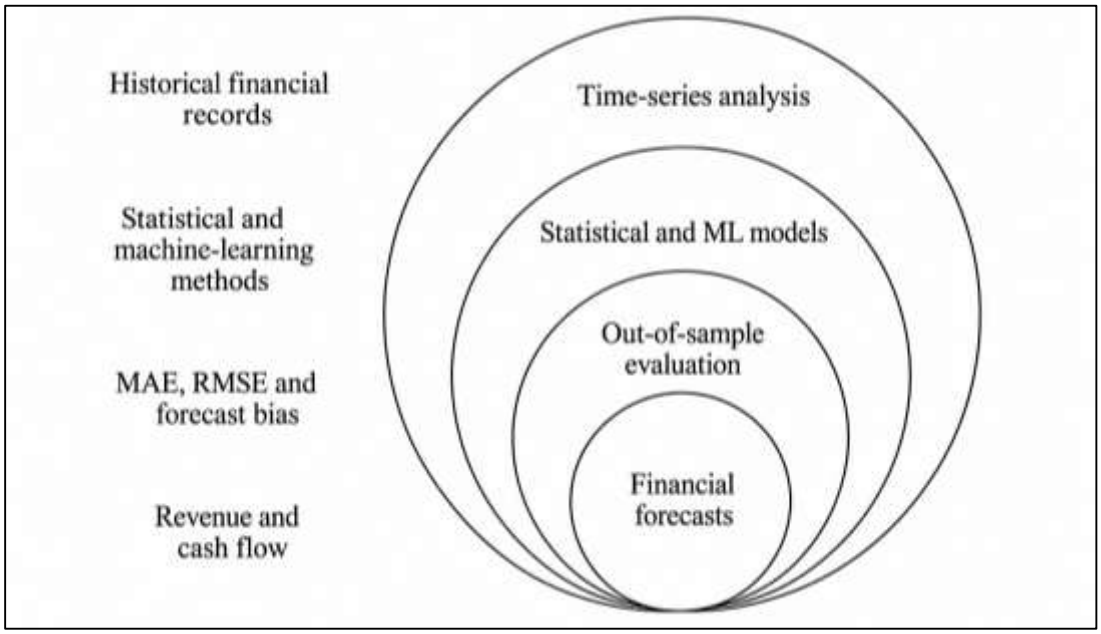
Quantitative investigations of generative artificial intelligence have identified numerical reasoning, factual consistency, arithmetic accuracy, and response reproducibility as distinct dimensions of model performance that require evaluation separately from linguistic fluency and textual coherence. Research by Brown and colleagues demonstrated the broad task capabilities of large language models, while studies by Bubeck and colleagues examined reasoning performance across mathematical, analytical, and professional tasks. Cobbe and colleagues introduced the GSM8K benchmark containing approximately 8,500 grade-school mathematics problems, establishing a structured dataset for evaluating multi-step numerical reasoning. Hendrycks and colleagues developed the MATH benchmark, comprising approximately 12,500 mathematical problems across different difficulty levels and subject areas, while Lewkowicz and colleagues investigated improvements in mathematical reasoning through specialized language-model training. Research by Wei and colleagues examined chain-of-thought prompting, and Kojima and colleagues investigated zero-shot reasoning strategies, demonstrating that response structure and prompting methods can influence numerical task performance (Fiorillo & Mehta, 2024; Jannatul, 2024). Additional studies by Chen and colleagues on program-aided language models and Gao and colleagues on program-aided reasoning examined the separation of natural-language reasoning from executable mathematical computation. Research by Ji and colleagues synthesized hallucination-related problems in natural language generation, while investigations by Lin, Hilton, and Evans examined truthfulness in language-model responses. These studies collectively indicate that producing a plausible numerical explanation does not independently establish the correctness of the underlying calculation. Within financial planning, numerical reliability involves arithmetic consistency, correct interpretation of accounting relationships, agreement between reported totals and source records, and the stability of calculated outcomes under repeated analytical conditions. A generated financial narrative may accurately describe a cash-flow problem while presenting an incorrect balance, inconsistent percentage change, or unsupported financial assumption. Consequently, financial calculation accuracy requires comparison with independently verified numerical results rather than reliance on the apparent completeness of generated explanations (Kynatun & Saba, 2024; Malik et al., 2023). Empirical assessment can examine exact-match accuracy, absolute numerical discrepancies, arithmetic error frequency, unsupported numerical statements, reconciliation differences, and the percentage of responses satisfying predefined financial constraints. Repeated-response evaluation can also identify variation in generated financial values when identical accounting information and instructions are submitted under comparable conditions. Studies involving mathematical reasoning and tool-assisted computation demonstrate important methodological differences between language models performing calculations internally and systems delegating numerical operations to external computational tools. These distinctions are particularly relevant to small-business financial planning, where budgeting, liquidity assessment, profitability estimation, and financial scenario analysis depend on numerical consistency across interconnected financial variables. The available literature therefore separates general generative AI task performance from domain-specific financial reliability, emphasizing verified calculations, reproducibility, and the accurate interpretation of accounting information as measurable components of analytical performance (Alsaedi et al., 2024; Kynatun & Saba, 2024).

Comparative Quantitative Performance of Generative AI-Assisted Financial Forecasting and Conventional Predictive Models

Quantitative research on financial forecasting has established a substantial empirical foundation for evaluating conventional statistical models across sales revenue, operating expenditure, profitability, cash-flow movements, working-capital requirements, and financing needs. Earlier forecasting

investigations by Marinakis and Habon, Marinakis and colleagues, Gardner, Hyndman and Khandakar, and Fildes and colleagues examined the predictive performance of moving averages, exponential smoothing, autoregressive integrated moving average models, seasonal forecasting procedures, and regression-based techniques across heterogeneous time-series datasets (Hassani & Silva, 2024; Mashiat, 2024). The M3 forecasting competition evaluated 3,003 time series, providing extensive comparative evidence concerning forecasting performance across annual, quarterly, monthly, and other observation frequencies. The M4 competition subsequently expanded the evaluation to 100,000 time series, incorporating a wider range of statistical, computational, and hybrid forecasting methods. These investigations demonstrated that forecasting accuracy varies according to data frequency, seasonality, trend characteristics, historical observation length, and forecast horizon, with no conventional method consistently outperforming alternatives across every dataset. Research by Gardner on exponential smoothing established the relevance of trend and seasonal adjustments, while Hyndman and Khandakar examined automated model identification and statistical forecasting procedures. Studies by Fildes and colleagues investigated forecasting practices in organizational environments, including the influence of judgmental adjustments and the quality of managerial forecasting processes. Within small-business financial planning, conventional models have been applied to sales projections, expenditure estimation, cash-flow forecasting, and demand-related financial planning. Weekly forecasts frequently involve short-term transaction variability and operational cash requirements, while monthly and quarterly projections incorporate seasonal revenue patterns, supplier payment schedules, and recurring expenditure obligations (Sumaiya, 2024; Taherdoost & Madanchian, 2023).

Figure 5: Comparative financial forecasting model framework



Annual forecasts generally involve longer planning horizons and greater uncertainty regarding economic conditions, investment decisions, and financing arrangements. Forecasting performance has commonly been evaluated through mean absolute error, root mean squared error, mean absolute percentage error, symmetric mean absolute percentage error, and forecast bias. These indicators capture different dimensions of predictive accuracy, with absolute-error measures reflecting average deviations, squared-error measures assigning greater weight to larger errors, and percentage-based measures facilitating comparisons across differently scaled financial series when their denominators are appropriate. Comparative studies have also examined model stability, parameter sensitivity, and differences between in-sample fitting and out-of-sample predictive performance. The synthesized

evidence indicates that conventional statistical methods provide important benchmarking approaches for financial forecasting, particularly when historical financial records exhibit stable trends, recurring seasonal patterns, and sufficient observation continuity (Nguyen et al., 2024; Feroz, 2024). However, the broader forecasting competition datasets contain many nonfinancial series, requiring careful distinction between general forecasting performance and empirical results obtained specifically from small-business accounting and financial records.

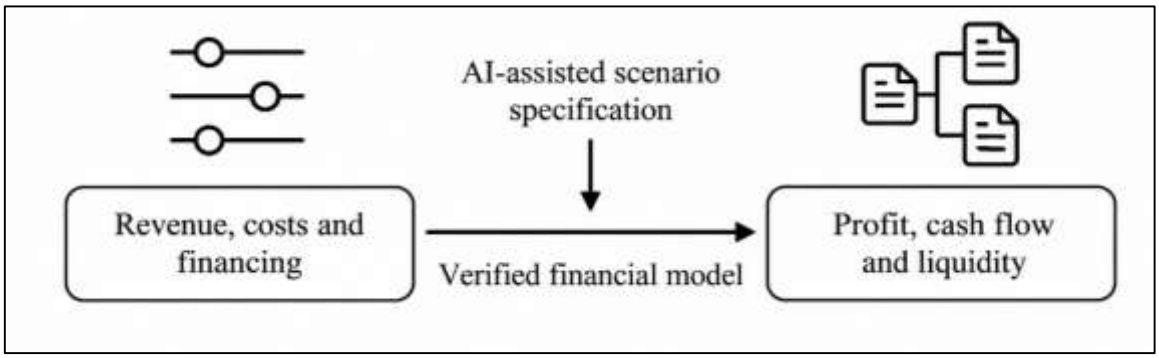
Empirical research on machine-learning-based forecasting has examined whether nonlinear computational models provide measurable improvements over conventional statistical techniques when financial and business datasets contain complex relationships, irregular fluctuations, multiple explanatory variables, and changing temporal patterns. Studies by Zhang investigated hybrid autoregressive and neural-network forecasting, while research by Khazei and Bihari examined artificial neural networks and combined forecasting approaches for nonlinear time-series prediction. Additional investigations by Crone and colleagues, Ahmed and colleagues, and Tayeb and colleagues compared machine-learning methods across forecasting datasets, identifying differences in predictive accuracy associated with model configuration, data characteristics, and forecast horizons (Naqbi et al., 2024; Jahanara, 2025). Research by Smyl introduced a hybrid approach combining exponential smoothing and recurrent neural networks, achieving the strongest overall performance in the M4 forecasting competition. Studies by Bandara and colleagues examined recurrent neural networks for forecasting groups of related time series, while research by Salinas and colleagues investigated probabilistic forecasting using autoregressive recurrent neural networks. Lim and colleagues developed the Temporal Fusion Transformer for interpretable multi-horizon forecasting, and Ovechkin and colleagues introduced N-BEATS, a neural forecasting architecture evaluated against established forecasting benchmarks. These studies collectively demonstrate that machine-learning performance depends on training sample size, feature composition, temporal structure, hyperparameter selection, and the degree of similarity between training and testing observations. Random forest and gradient boosting approaches have been applied to tabular forecasting problems involving historical values, lagged predictors, seasonal indicators, and external explanatory variables, while support vector regression has been examined for nonlinear relationships in comparatively structured datasets (Cao et al., 2024; Jannatul, 2025). Boost has been investigated for predictive modeling involving interactions among multiple input variables, whereas long short-term memory networks and other recurrent architectures have been used to capture sequential dependencies. Financial forecasting applications include revenue estimation, market-related prediction, demand forecasting, cash-flow modeling, and financial risk assessment, although evidence from financial markets cannot automatically be generalized to small-business operational accounting. The comparative performance of these methods has been assessed using MAE, RMSE, MAPE, symmetric MAPE, forecast bias, and R^2, with evaluation procedures ranging from fixed chronological holdout samples to rolling-origin validation. Differences in reported forecasting accuracy frequently reflect variation in prediction horizons, dataset scale, model tuning, and benchmark selection rather than algorithm architecture alone. Research on global forecasting models has additionally examined whether learning across multiple related series provides advantages when individual businesses possess relatively short historical records (Cho et al., 2023; Mostari, 2025). The empirical literature therefore identifies machine-learning forecasting as a heterogeneous methodological category, with predictive performance requiring evaluation against appropriately configured statistical baselines and independent observations representing the intended financial planning environment.

AI-Assisted Financial Scenario Generation and Uncertainty Modeling

Quantitative research on financial scenario analysis has established that structured comparisons of alternative economic and operational conditions provide an important methodological foundation for examining business profitability, liquidity, cash-flow variability, financing requirements, and financial risk exposure. Empirical and simulation-based investigations by Hertz, Ho and Pike, Graham and Harvey, Poornanand, and Campello and colleagues have examined financial uncertainty, investment appraisal, corporate financial policies, and organizational responses to changing economic conditions (Mashfiqur, 2025; Yazdi et al., 2024). These studies have employed different combinations of scenario analysis, sensitivity testing, survey-based financial assessment, and quantitative modeling to

investigate how variations in financial assumptions are associated with business outcomes. Research by Graham and Harvey, based on responses from 392 chief financial officers, documented the use of financial evaluation techniques in corporate decision-making, while Campello and colleagues examined financing constraints and financial policies during periods of economic instability. Although these studies primarily involved corporate financial management rather than generative AI-assisted small-business planning, they provide established empirical foundations for examining the financial variables incorporated into scenario-based decision processes. Financial scenario structures have generally included baseline projections representing expected operating conditions, optimistic scenarios incorporating favorable revenue or cost assumptions, pessimistic scenarios reflecting adverse operating conditions, and stress scenarios involving more substantial financial disturbances (Blanco et al., 2024; Mashiat, 2025). Multi-variable scenarios have additionally considered simultaneous changes in sales volume, product pricing, labor expenditure, supplier costs, borrowing rates, inflation, exchange rates, and working-capital requirements. Quantitative financial outcomes have been represented through projected net profit, operating margins, operating cash flow, cash reserves, current ratios, debt-service capacity, break-even sales, and external financing needs. The analytical relationships among these variables depend on enterprise cost structures, revenue concentration, inventory requirements, payment arrangements, and financial leverage.

Figure 6: Financial scenario and sensitivity analysis



Small businesses frequently exhibit greater sensitivity to individual customers, suppliers, and financing arrangements because their operating activities may be concentrated across fewer revenue sources and financial relationships. Comparative scenario studies have evaluated the distribution of financial outcomes under alternative assumptions, with changes in profitability and liquidity interpreted in relation to the magnitude of underlying financial disturbances. Financial modeling research has also examined the distinction between single-variable scenarios and combined economic shocks, demonstrating that interactions among revenue, expenditure, and financing assumptions can produce outcomes that differ from isolated sensitivity estimates (Dempere et al., 2024; Arif Uz et al., 2025). Within generative AI-assisted financial planning, these established scenario structures provide measurable reference conditions for evaluating the accuracy, consistency, and completeness of automatically generated financial alternatives. However, conventional scenario-modeling evidence remains analytically distinct from direct empirical demonstrations of generative AI performance, particularly when financial outcomes originate from verified computational models rather than calculations performed independently by language models.

Empirical investigations of financial sensitivity analysis have examined the extent to which changes in economic assumptions, operational conditions, and financing variables influence profitability, cash-flow adequacy, investment outcomes, and financial stability. Research by Santelli and colleagues established comprehensive methodological approaches for sensitivity analysis, while studies by Sobol and Morris developed quantitative procedures for evaluating the influence of model inputs on calculated outcomes (Luo, et al., 2024; Pervaz, 2025). Additional investigations by Organovo examined moment-independent sensitivity measures, and research by Pianos and colleagues synthesized approaches for assessing parameter importance, uncertainty, and model response behavior. These

methodological contributions have been applied across financial, economic, engineering, and risk-analysis settings, although their original empirical applications were not uniformly concerned with small-business financial planning. Within corporate financial research, studies by Fazzari, Hubbard, and Petersen examined relationships among financing constraints, investment, and internal cash flow, while Almeida, Campello, and Weisbach investigated corporate cash holdings and financial constraints. Research by García-Teruel and Martínez-Solano and Baños-Caballero and colleagues examined working-capital management and profitability, providing quantitative evidence concerning the financial relevance of receivables, inventory, and payment arrangements (Chairat & Gheewala, 2024; Sumaiya, 2025). These studies collectively establish that financial performance is associated with multiple interacting variables rather than isolated changes in revenue or expenditure. Scenario-based sensitivity analysis has commonly assessed how specified changes in sales revenue, unit prices, material costs, wages, interest rates, and payment periods affect net profit, cash reserves, break-even requirements, and financing needs. One-factor-at-a-time procedures isolate the influence of individual assumptions, while multivariable approaches evaluate combined disturbances and interactions among financial inputs. Regression analysis has been used to estimate relationships between explanatory variables and financial outcomes, whereas variance-based sensitivity procedures quantify the contribution of uncertain inputs to variation in model-generated results. Analysis of variance and factorial experimental designs can additionally examine differences among predefined scenario conditions when the analytical design supports such comparisons. Financial sensitivity coefficients, standardized regression estimates, confidence intervals, and explained variance provide complementary information about the direction, magnitude, and statistical reliability of observed relationships. The interpretation of these measures requires distinguishing empirical associations estimated from business observations from deterministic changes calculated within a financial model (Osorio et al., 2024; Feroz, 2025). A simulated increase in operating costs, for example, generates a model-dependent change in projected profit, whereas an observed relationship between costs and profitability may reflect additional organizational and economic influences. Generative AI-assisted scenario systems introduce another dimension by supporting the interpretation and organization of financial assumptions through natural-language instructions. Their performance can be evaluated through the correctness of translated assumptions, consistency of variable changes, and agreement between generated explanations and independently calculated sensitivity results. The synthesized evidence therefore differentiates established sensitivity-analysis methods from the emerging application of generative AI interfaces to financial scenario specification and interpretation.

Quantitative research on uncertainty modeling has established Monte Carlo simulation, probabilistic forecasting, stochastic financial modeling, and distribution-based risk assessment as important approaches for examining variation in financial outcomes under uncertain economic and operational conditions (Ahmed, 2026; Maceika et al., 2024). Foundational research by Metropolis and Ulam established the computational principles of Monte Carlo methods, while Hertz demonstrated their application to risk analysis in capital investment decisions. Subsequent studies by Boyle examined Monte Carlo approaches to financial option valuation, and research by Glasser man provided a comprehensive treatment of simulation methods in financial engineering. Studies by Jarion investigated financial risk measurement, while research by Arzner and colleagues examined quantitative properties of financial risk measures. Additional investigations by Gneiting and Raftery established statistical principles for evaluating probabilistic forecasts, and research by Salinas and colleagues examined deep-learning-based probabilistic forecasting across heterogeneous time-series datasets. These investigations collectively demonstrate that uncertainty modeling differs from deterministic scenario analysis because it represents uncertain variables through probability distributions and evaluates the resulting variation in calculated outcomes. In financial planning, probabilistic inputs may include sales demand, customer payment timing, operating expenditure, inventory costs, interest rates, exchange rates, and financing availability. Repeated simulation generates distributions of projected net profit, operating cash flow, cash reserves, and external financing requirements rather than relying exclusively on individual baseline or stress scenarios. Relevant quantitative outputs include expected financial outcomes, distributional dispersion, lower-tail cash-flow estimates, probabilities of liquidity shortfalls, and prediction intervals (Chiaburu et al.,

2024; Jahanara, 2026). Monte Carlo analysis also permits examination of correlations among financial inputs, including relationships between sales demand and inventory investment or between borrowing costs and debt-service requirements. The reliability of simulated outcomes depends on the appropriateness of input distributions, parameter estimates, dependency assumptions, and the quality of historical financial information. Empirical research has examined simulation stability, distributional calibration, forecast coverage, and sensitivity to alternative parameter specifications. In small-business settings, limited historical records, irregular cash transactions, seasonal revenue patterns, and concentrated customer relationships can complicate the estimation of reliable probability distributions. Generative AI-assisted analytical systems may support the identification of relevant uncertainty factors, interpretation of probabilistic results, and preparation of financial scenario narratives, while numerical simulations require verified computational procedures. Studies involving time-series foundation models and language-model-assisted analytical workflows have explored computational approaches to prediction and interpretation, but their reported forecasting performance does not independently establish the calibration or financial validity of AI-generated scenario distributions (Jannatul, 2026; Nguyen et al., 2023). Comparative quantitative assessment therefore distinguishes probabilistic forecasting accuracy from linguistic explanation quality and evaluates whether generated descriptions accurately represent simulated financial outcomes. Across the reviewed research, uncertainty modeling is characterized by explicit assumptions, distributional analysis, statistical validation, and the measurement of downside financial exposure, with particular emphasis on the consistency between financial input conditions and resulting outcome distributions.

Empirical research on computational decision support, generative artificial intelligence, and financial modeling has identified scenario reliability, numerical accuracy, processing efficiency, and reproducibility as separate dimensions of analytical performance. Studies by Noy and Zhang, Brynjolfsson, Li, and Raymond, Peng and colleagues, and Belacqua and colleagues examined the influence of generative AI assistance on professional task performance, reporting measurable differences in completion time, productivity, and output quality across experimental or organizational settings (Behzadan, et al., 2024; Mashfiqur, 2026). Noy and Zhang reported an approximately 40% reduction in average task-completion time and an approximately 18% improvement in evaluated output quality for the writing tasks studied, while Brynjolfsson and colleagues identified an average productivity improvement of approximately 14% among customer-support agents using AI assistance. These findings provide quantitative evidence concerning generative AI-supported information processing but do not directly measure the accuracy or financial feasibility of AI-generated business scenarios. Research by Cobbe and colleagues, Hendrycks and colleagues, and Chen and colleagues examined mathematical reasoning, numerical problem-solving, and program-assisted computation, demonstrating important distinctions between language-model-generated reasoning and externally verified calculations. Additional investigations by Ji and colleagues and Lin and colleagues examined hallucination and factual reliability, identifying limitations associated with unsupported statements and inconsistencies in generated information. Within financial scenario analysis, reliability can be measured through assumption consistency, arithmetic correctness, adherence to financial constraints, reconciliation of projected statements, and agreement with independently verified numerical outputs. Scenario reproducibility concerns the stability of results across repeated analytical runs, while financial feasibility involves satisfying relevant accounting relationships, liquidity restrictions, borrowing limits, and operating conditions (Li et al., 2024; Rony & Md, 2026).

Quantitative scenario efficiency can be represented by the number of valid scenarios produced, average processing time per scenario, analytical coverage of specified financial variables, and the proportion of outputs requiring manual correction. Comparative evaluation can involve conventional spreadsheet-based scenario modeling, statistical simulation systems, machine-learning-assisted analytical procedures, and generative AI-supported interfaces connected to verified financial engines. Paired-samples tests can assess differences in task completion or calculation accuracy when the same financial scenarios are evaluated using alternative methods, while ANOVA and nonparametric comparisons can examine differences across multiple analytical configurations. Regression analysis can evaluate associations among dataset quality, scenario complexity, processing time, and numerical reliability, with standardized coefficients, confidence intervals, and effect sizes supporting interpretation of the

observed relationships. Repeated testing and independent verification are particularly important because an analytically fluent scenario description may contain incorrect financial assumptions or inconsistent calculations. The integrated literature indicates that conventional simulation and sensitivity-analysis methods provide established quantitative standards for financial scenario evaluation, while generative AI research contributes evidence concerning information processing, task efficiency, and numerical reasoning limitations (Elgin & Elgin, 2024; Sumaiya, 2026). Direct comparative evidence involving generative AI-assisted small-business financial scenarios remains relatively limited, and the available studies address different combinations of financial modeling, computational performance, and organizational decision support rather than a single standardized measure of scenario effectiveness.

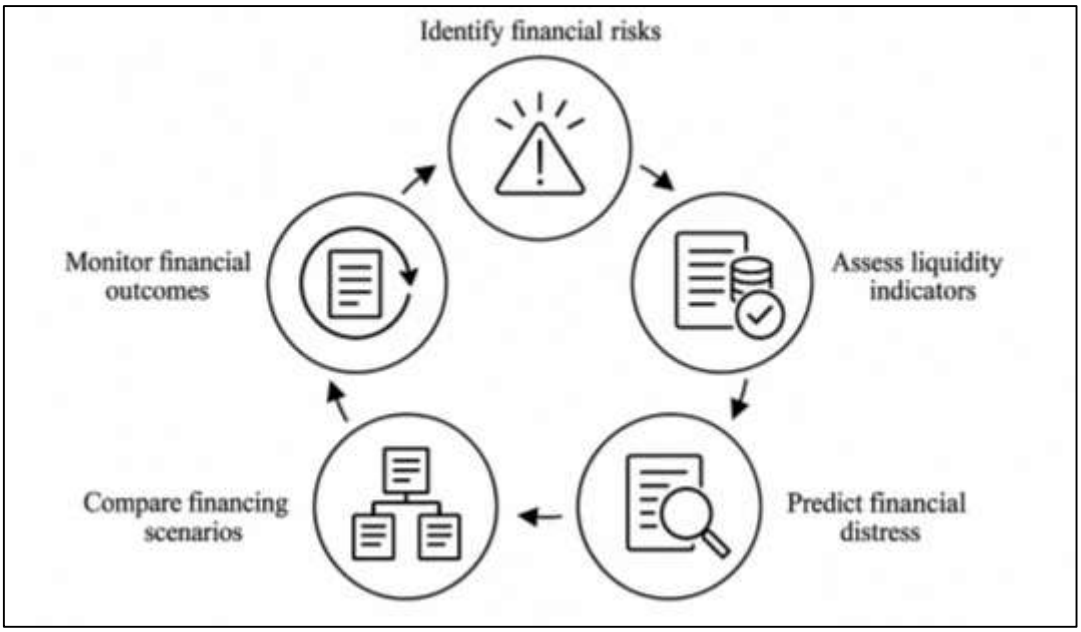
AI-Assisted Financial Planning and Small-Business Financial Risk

Quantitative research on small-business financial management has established substantial empirical relationships among liquidity conditions, working-capital efficiency, cash-flow stability, and organizational financial performance. Studies by Deloof, García-Teruel and Martínez-Solano, Lazaridis and Tryfonidis, Rahaman and Nasr, and Baños-Caballero and colleagues examined the relationships between working-capital components and profitability across different enterprise samples, industries, and national economic environments (Drydakis, 2022). Deloof analyzed 1,009 large Belgian nonfinancial firms and identified significant associations between profitability and the management of accounts receivable, inventories, and accounts payable. García-Teruel and Martínez-Solano investigated 8,872 Spanish small and medium-sized enterprises, reporting that shorter receivables collection periods and inventory holding periods were associated with improved profitability. Research by Lazaridis and Trigoniids examined 131 companies listed on the Athens Stock Exchange, while Rahaman and Nasr analyzed 94 Pakistani firms and reported statistically significant relationships between working-capital management indicators and profitability. Additional studies by Afrifa, Enqvist and colleagues, and Baños-Caballero and colleagues examined liquidity management, working-capital investment, and financial performance under varying organizational and economic conditions (Boffa, 2023). Across these investigations, liquidity has been represented through current ratios, quick ratios, cash holdings, and operating cash-flow measures, while working-capital efficiency has been evaluated using cash conversion cycles, inventory turnover, receivables collection periods, and accounts payable periods. Empirical findings generally indicate that excessive capital tied to inventories and receivables can be associated with lower profitability, although very restrictive working-capital policies can also increase operational and liquidity risks. Research by Baños-Caballero and colleagues identified evidence consistent with a nonlinear relationship between working-capital investment and profitability, indicating that financial performance may depend on maintaining an appropriate balance between liquidity and operating requirements. Statistical approaches have included Pearson correlations, multiple regression, fixed-effects estimation, and panel-data models incorporating firm size, leverage, sales growth, and industry characteristics (Clampit et al., 2021). These methods have generated regression coefficients, statistical significance estimates, and measures of explained variation, although coefficient magnitudes differ according to financial definitions, sample characteristics, and estimation procedures. The findings establish a quantitative foundation for evaluating AI-assisted financial planning because cash-flow projections, liquidity monitoring, and working-capital scenario analysis depend on the same financial relationships. However, the reported profitability associations originated primarily from conventional financial management studies and should not be interpreted as direct evidence that generative AI utilization improves liquidity or financial performance.

Empirical investigations of financial constraints and business risk have examined how cash-flow variability, financing accessibility, debt obligations, revenue instability, and economic uncertainty influence financial decisions and organizational performance. Research by Fazzari, Hubbard, and Petersen established an influential empirical framework for examining investment and internal financing relationships, while studies by Kaplan and Zingales questioned the interpretation of investment–cash-flow sensitivity as a direct measure of financing constraints (Rink, 2024). Almeida, Campello, and Weisbach subsequently examined the relationship between financial constraints and corporate cash-saving behavior, identifying differences in cash management associated with financing

conditions.

Figure 7: Financial planning and risk management



Studies by Beck, Demiurgic-Kunt, and Maksimovic investigated the relationships among financial constraints, firm size, and growth, while research by Berger and Udell examined the financing structures and credit relationships of small businesses. Additional investigations by Petersen and Rajan, Carpenter and Petersen, and Cowling and colleagues examined lending relationships, financing limitations, and the financial conditions influencing enterprise development. These studies provide quantitative evidence that financial risk depends on interactions among internally generated funds, external credit accessibility, borrowing costs, collateral requirements, and business operating characteristics. Small businesses frequently experience concentrated revenue sources, uneven customer payment patterns, limited financial reserves, and restricted access to alternative financing channels, contributing to measurable differences in cash-flow volatility and debt-servicing capacity. Financial risk has been evaluated through leverage ratios, interest coverage, debt-service coverage, negative operating cash flow, cash reserve adequacy, payment delays, and indicators of credit constraints (Naysary & Tarazi, 2024). Revenue volatility and expenditure variability have also been examined as determinants of liquidity uncertainty, particularly when operating expenses remain relatively fixed while sales fluctuate. Statistical investigations have employed correlation analysis, multiple regression, logistic regression, and panel-data estimation to assess associations between financial characteristics and financing outcomes. Logistic models have been used to evaluate binary outcomes such as credit approval, financing constraints, and financial distress classification, while panel regression has examined financial relationships across repeated enterprise observations. Reported coefficients, odds ratios, marginal effects, and confidence intervals depend on the operational definitions of financial constraints and the characteristics of the sampled firms. The broader evidence indicates that financial risk is multidimensional and cannot be adequately represented by leverage or cash holdings alone. Within AI-assisted financial planning, these relationships correspond to measurable analytical tasks involving cash-flow shortfall identification, financing scenario comparison, borrowing-cost sensitivity, and liquidity stress assessment. The reviewed studies establish the financial risk variables and statistical relationships relevant to these applications, while direct evidence linking generative AI adoption to reduced financing constraints or lower observed default rates remains substantially more limited (Frey, 2021).

Quantitative research on financial distress prediction has established a substantial methodological foundation for assessing the classification accuracy, predictive reliability, and statistical determinants of business failure and financial instability. Foundational studies by Beaver examined financial ratios as predictors of corporate failure, while Altman developed a multivariate discriminant approach to bankruptcy prediction using accounting-based financial indicators. Ohlson subsequently investigated probabilistic bankruptcy prediction through logistic regression, and Zmijewski examined methodological issues associated with financial distress prediction and sample selection. Later studies by Shumway evaluated hazard-based bankruptcy prediction, while research by Chava and Jarrow investigated bankruptcy forecasting using financial and market-related explanatory variables (Qiu et al., 2024). Artificial intelligence and machine-learning investigations extended these approaches through nonlinear classification methods, including artificial neural networks, support vector machines, decision trees, random forests, and ensemble learning. Studies by Tam and Kiang compared neural-network approaches with conventional statistical techniques in bank failure prediction, while Min and Lee examined support vector machines for bankruptcy prediction. Research by Sun and colleagues reviewed financial distress prediction methods, and studies by Barboza, Kimura, and Altman compared machine-learning techniques with traditional statistical models for corporate bankruptcy prediction. These investigations have evaluated financial indicators including profitability, liquidity, leverage, retained earnings, cash-flow adequacy, working-capital ratios, and debt-servicing measures. Predictive performance has commonly been assessed through classification accuracy, sensitivity, specificity, precision, recall, F1-score, and the area under the receiver operating characteristic curve (Clampit et al., 2021). The results demonstrate that model performance varies according to sample composition, class imbalance, predictor selection, observation periods, and the definition of financial distress. In small-business environments, the application of these methods can be complicated by limited historical financial statements, incomplete accounting records, and differences between formal bankruptcy events and temporary liquidity difficulties. Financial distress classification also differs from short-term cash-flow warning identification because an enterprise may experience a temporary liquidity shortfall without meeting the criteria for insolvency or bankruptcy. AI-assisted liquidity monitoring can therefore be evaluated through the identification of negative projected cash balances, repayment difficulties, unusual expenditure patterns, and deteriorating financial ratios. Generative AI systems may assist with interpreting risk classifications, explaining financial warning indicators, and organizing alternative financing scenarios, while verified statistical or machine-learning models provide the underlying numerical risk estimates. The reviewed empirical studies primarily evaluate conventional statistical and predictive machine-learning systems rather than generative AI-specific financial risk applications (Baddal et al., 2024). Consequently, the evidence supports comparisons of predictive classification performance and financial indicator relevance without establishing that conversational generative AI independently produces superior distress predictions or more accurate liquidity warnings.

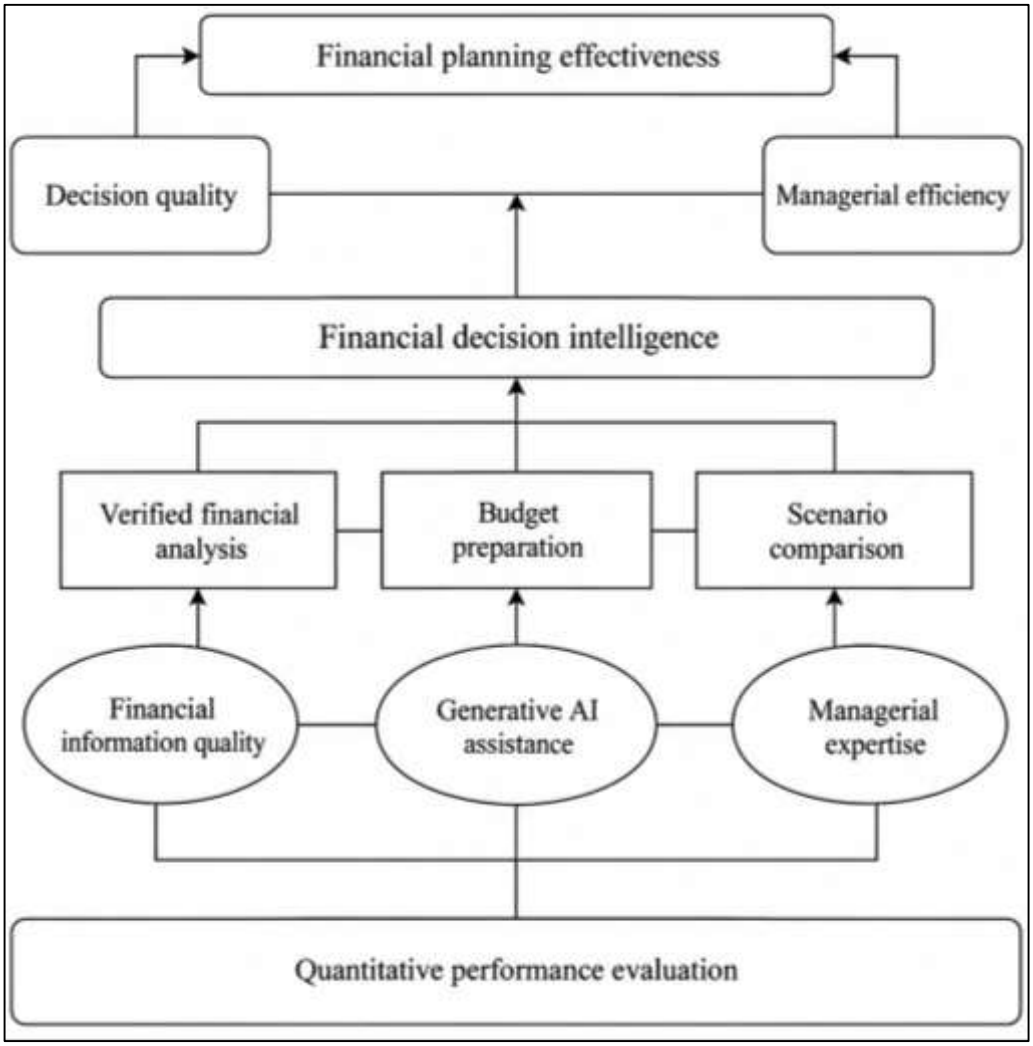
The integrated quantitative literature on financial analytics, working-capital management, risk prediction, and organizational performance demonstrates that financial information quality, analytical capabilities, liquidity conditions, and financing constraints represent interconnected but analytically distinct determinants of small-business financial outcomes. Research by Chen, Chiang, and Storey established a foundation for understanding business intelligence and analytics, while studies by Gupta and George, Wamba and colleagues, and Mikalef and colleagues examined relationships among analytical capabilities, organizational resources, information processing, and business performance (Malik et al., 2024). These investigations complement financial management studies by García-Teruel and Martínez-Solano, Afrifa, Baños-Caballero and colleagues, and Enqvist and colleagues, which identified associations between working-capital indicators and profitability. Research on financial constraints by Beck and colleagues, Almeida and colleagues, and Carpenter and Petersen further demonstrated that financing conditions and internal liquidity can influence investment behavior and enterprise financial flexibility. Meanwhile, studies by Altman, Ohlson, Shumway, Min and Lee, and Barboza and colleagues established statistical and machine-learning approaches for identifying financial distress using accounting and financial indicators. Together, these research streams provide empirical support for examining financial planning as a process involving information availability,

financial forecasting, liquidity assessment, risk identification, and managerial decision-making. However, the studies differ substantially in their research designs, measurement approaches, sample characteristics, and outcome definitions. Financial management investigations commonly use observed profitability, liquidity ratios, and working-capital measures, while financial distress prediction studies emphasize classification performance and the discrimination between distressed and nondistressed enterprises (Elahi et al., 2023). Business analytics research frequently measures technological capabilities, organizational readiness, and perceived or observed performance, creating additional differences in construct measurement. Quantitative integration therefore requires distinguishing relationships derived from observed business financial records from performance differences measured in computational experiments. Correlation coefficients can identify associations among liquidity indicators, planning practices, and financial outcomes, while multiple regression can assess their relationships after accounting for enterprise size, industry, leverage, and revenue characteristics. Logistic regression can examine financial distress probabilities, and panel-data methods can account for repeated financial observations and unobserved enterprise heterogeneity. Statistical interpretation can incorporate standardized coefficients, odds ratios, marginal effects, confidence intervals, effect sizes, and explained variance, although these measures should not be compared directly without considering their underlying models and scales. Generative AI-assisted financial planning introduces additional measurable variables, including AI utilization intensity, forecasting reliability, scenario-analysis consistency, risk explanation accuracy, and financial task-processing efficiency. Evidence from generative AI productivity research supports the examination of computational assistance in professional tasks, but it does not establish direct improvements in liquidity ratios, profitability, or business survival (Allahqoli et al., 2022). The synthesized literature therefore identifies a clear methodological distinction between the established statistical relationships governing small-business financial risk and the more limited direct empirical evidence concerning generative AI-assisted liquidity management, financing decisions, and financial risk reduction.

Financial Decision Intelligence and Organizational Performance

Quantitative research on financial decision intelligence has established that analytical information quality, computational decision support, managerial expertise, and technological capabilities are associated with measurable differences in decision accuracy, judgment consistency, and the evaluation of organizational alternatives. Empirical investigations by Goodhue and Thompson, Delone and McLean, Wixom and Watson, Popovic and colleagues, and Gupta and George examined relationships among information-system effectiveness, analytical capabilities, information accessibility, and organizational decision processes (Wang et al., 2022). Goodhue and Thompson investigated task–technology fit and its relationship with individual performance, while Wixom and Watson examined determinants of data warehousing success and the organizational conditions influencing analytical information utilization. Research by Popovic and colleagues investigated business intelligence system maturity, information quality, and analytical decision-making, while Gupta and George examined the organizational resources associated with big data analytics capabilities. Additional investigations by Wamba and colleagues and Micallef and colleagues identified relationships among analytical capabilities, organizational resources, and business performance using survey-based quantitative models. These studies provide empirical foundations for examining financial decision intelligence, although their original analytical settings were not exclusively concerned with generative AI-assisted financial planning. More recent experimental research by Noy and Zhang, Belacqua and colleagues, and Brynjolfsson, Li, and Raymond examined generative AI-assisted professional activities and identified measurable differences in task performance, output quality, and worker productivity. Belacqua and colleagues studied 758 consultants and reported improvements in several task-performance measures when participants received AI assistance on tasks within the technology's effective capability range, while also identifying performance limitations for tasks outside that range (Niu et al., 2021).

Figure 8: Financial decision intelligence and efficiency



These findings demonstrate that AI assistance can influence professional judgments and task execution, but the magnitude and direction of performance differences depend on task characteristics and the reliability of generated information. Within small-business financial planning, decision quality can be operationalized through the accuracy of budget selections, identification of liquidity risks, consistency of investment judgments, and selection of financially feasible alternatives. Financial decision accuracy can be assessed by comparing managerial choices with independently verified financial outcomes or predefined decision criteria, while consistency can be evaluated through repeated financial tasks under equivalent information conditions. Studies involving business intelligence and decision-support systems have employed regression analysis, structural equation modeling, and comparative statistical procedures to examine relationships among information quality, technological utilization, and decision performance. Standardized regression coefficients, explained variance, confidence intervals, and significance levels provide measures of association, although perceived decision quality and objectively evaluated financial judgment accuracy represent distinct outcomes (Ragazou et al., 2023). The synthesized evidence establishes that financial decision intelligence encompasses both the analytical correctness of financial information and the ability of managers to interpret that information when comparing business alternatives, with direct generative AI-specific evidence in small-business financial decisions remaining more limited than the broader business intelligence literature.

Empirical research on artificial intelligence-assisted professional activities has demonstrated measurable relationships between computational assistance, task-completion efficiency, information-processing speed, and the quality of analytical outputs. Noy and Zhang conducted a controlled

experiment involving 444 college-educated professionals and reported that access to ChatGPT reduced average task-completion time by approximately 40% while improving evaluated output quality by approximately 18% for the writing assignments examined. Brynjolfsson, Li, and Raymond analyzed generative AI assistance among 5,179 customer-support agents and reported an average productivity increase of approximately 14%, with larger improvements among less experienced workers (Wamba-Taguimdje et al., 2020). Peng and colleagues investigated AI-assisted programming and found that participants using GitHub Copilot completed the assigned programming task approximately 55.8% faster than participants without the assistance. Belacqua and colleagues examined professional consulting activities and identified substantial improvements in task-completion speed and quality for assignments within the effective capabilities of generative AI, while reporting different performance patterns for tasks requiring capabilities beyond those boundaries. These experimental and organizational investigations provide quantitative evidence concerning generative AI-assisted task efficiency, although their results do not directly establish equivalent improvements in financial reporting, budgeting, or small-business profitability. Research on organizational decision-support technologies by Brynjolfsson and Hitt, Davenport and Harris, Elbasvir and colleagues, and Trieu has separately examined the relationships among information technology, business intelligence, analytical processes, and organizational performance. These studies identified the importance of organizational integration, information accessibility, and managerial utilization in interpreting technology-related performance differences. Within small-business financial planning, managerial efficiency can be evaluated through the average time required to prepare budgets, compare financial alternatives, interpret financial statements, assess liquidity conditions, and complete scenario-analysis tasks. Additional measures include financial reporting turnaround time, number of scenarios evaluated per decision, manual processing hours, and the proportion of financial outputs requiring correction (Nithya & Kiruthika, 2021). Financial planning effectiveness can be represented through budget variance, revenue forecast accuracy, cash-flow projection consistency, and the agreement between financial reports and verified accounting records. Comparative statistical investigations can use paired-samples tests to evaluate repeated tasks completed with and without AI assistance, while ANOVA can assess performance differences among conventional spreadsheets, statistical decision-support systems, and generative AI-assisted workflows. Hierarchical regression can examine whether AI utilization explains additional variation in task efficiency after accounting for managerial experience, financial literacy, enterprise size, and task complexity. The empirical literature also indicates that faster task completion and improved decision accuracy should be assessed separately because reductions in processing time may coexist with numerical errors, incomplete assumptions, or excessive reliance on generated explanations (Li & Zhang, 2024). Consequently, the quantitative evaluation of generative AI-assisted managerial efficiency involves the combined measurement of task duration, output accuracy, reporting reliability, and the financial relevance of completed analytical activities rather than productivity improvements alone.

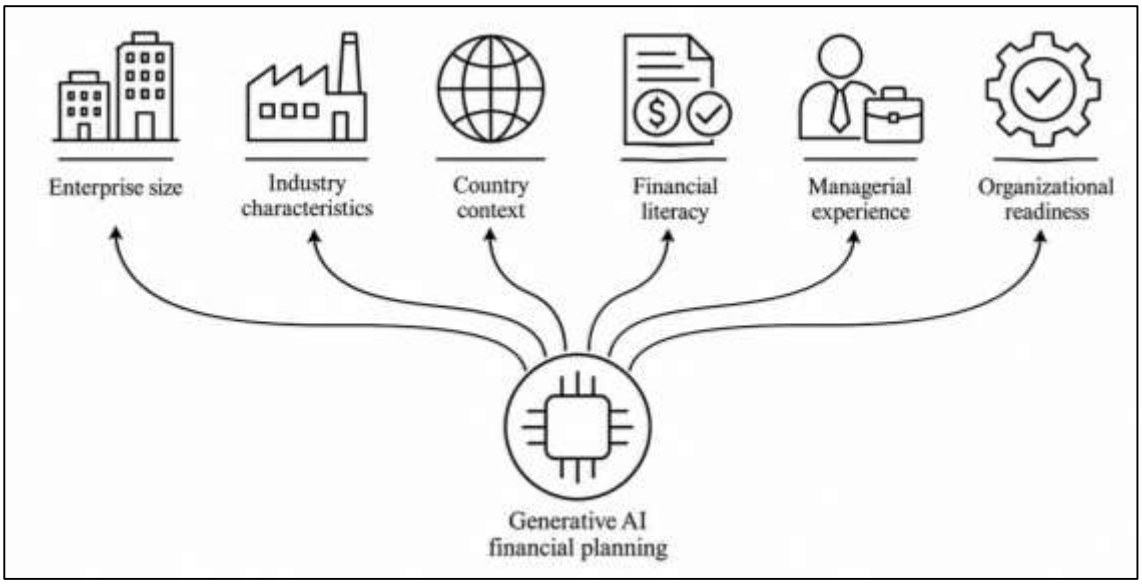
Differences in Generative AI Financial Planning Effectiveness

Quantitative research on enterprise digitalization and artificial intelligence adoption has established substantial differences in technological capabilities, financial management practices, and organizational performance across microenterprises, small businesses, and medium-sized enterprises. Empirical investigations by Beck, Demiurgic-Kunt, and Maksimovic; Ayyagari, Demiurgic-Kunt, and Maksimovic; Oliveira and Martins; Zhu and Kraemer; McLerran and colleagues; and Zolas and colleagues examined relationships among enterprise size, financial constraints, technological adoption, and organizational characteristics (Fan et al., 2022). These studies collectively identified differences in access to financial resources, specialized employees, digital infrastructure, and advanced analytical technologies across enterprise categories. Research by McLerran and colleagues, using firm-level evidence from the United States, documented that artificial intelligence adoption was concentrated among particular organizational groups and was associated with differences in firm size, workforce characteristics, and complementary technological capabilities. Studies by Zolas and colleagues similarly examined the diffusion of advanced technologies across American businesses, identifying considerable heterogeneity in the adoption of sophisticated computational systems. International enterprise surveys conducted through Eurostat and OECD research programs have also documented

differences in cloud computing, enterprise software, and artificial intelligence adoption between smaller and larger organizations. However, many technology surveys classify enterprises with fewer than ten employees separately or exclude them from selected reporting populations, creating limitations when comparing microenterprises with larger small businesses. Financial management studies by García-Teruel and Martínez-Solano, Afrifa, and Baños-Caballero and colleagues provide complementary evidence concerning differences in working-capital management, liquidity conditions, and profitability across smaller enterprises. These findings indicate that enterprise size is associated with variations in financial information availability, accounting-system sophistication, financial staffing, and the complexity of financial planning activities (Liang et al., 2023). Microenterprises commonly operate with limited accounting personnel and relatively simple financial records, while medium-sized enterprises may maintain more structured reporting systems, specialized financial management functions, and integrated business applications. Quantitative comparisons can assess adoption proportions, average technological utilization scores, financial reporting time, forecasting error, and scenario-analysis consistency across enterprise-size categories. Independent-samples tests, one-way ANOVA, ANCOVA, and multigroup regression provide methods for evaluating these differences, while interaction models can examine whether the relationship between AI utilization and financial planning performance varies according to enterprise size. Group means, standard deviations, standardized coefficients, effect sizes, and confidence intervals provide complementary measures of statistical and practical differences (Cao et al., 2024). The reviewed evidence establishes enterprise size as an important source of variation in technological readiness and financial management capability, although direct empirical comparisons of generative AI-assisted financial scenario performance across micro, small, and medium-sized enterprises remain considerably less developed than the broader literature on digital technology adoption.

Empirical research on digital transformation, business analytics, and organizational performance has identified substantial industry-level differences in technological adoption, financial information requirements, operational uncertainty, and analytical decision-making processes. Studies by Brynjolfsson and Hitt, Aral and colleagues, Chen, Chiang, and Story, Wamba and colleagues, and Micallef and colleagues examined relationships among information technology, analytics capabilities, organizational resources, and business performance across heterogeneous industry environments. Research by McLerran and colleagues and Zolas and colleagues further documented differences in advanced technology adoption across sectors, indicating that technological utilization is associated with organizational characteristics and the nature of production or service activities (Lim, 2024).

Figure 9: Financial planning across business contexts



Industry-specific forecasting research by Marinakis and colleagues, Salinas and colleagues, and Smyl examined predictive performance across datasets containing different temporal patterns, operational requirements, and forecasting horizons. The M5 forecasting competition incorporated 42,840 hierarchical retail sales time series, providing extensive quantitative evidence concerning forecasting performance under product-level, store-level, and category-level variation.

Although these observations primarily concern retail demand rather than financial planning, they establish relevant methodological evidence for evaluating revenue forecasting and inventory-related financial requirements. Retail enterprises frequently require forecasts of product demand, sales revenue, inventory expenditure, and supplier payments, while manufacturing businesses incorporate production costs, raw-material prices, equipment expenditure, and working-capital requirements. Hospitality businesses experience additional variation associated with occupancy, seasonal demand, labor scheduling, and operating expenses. Professional service firms often depend on project-based revenue, employee utilization, client payment periods, and comparatively limited physical inventory (Johnson et al., 2022). Information technology and digital commerce enterprises may maintain extensive electronic transaction records, while logistics businesses frequently evaluate transportation costs, fuel expenditure, delivery demand, and fleet-related financial commitments. These operational differences influence the financial variables available for forecasting and the complexity of scenario-analysis procedures. Generative AI-assisted financial planning can be examined through industry-specific measures of task coverage, data integration, forecast accuracy, scenario validity, and analytical processing time. However, industry variation in AI adoption does not independently demonstrate differences in the financial accuracy of generative AI systems. Comparative statistical studies can use factorial ANOVA to examine the combined relationships of industry classification and AI utilization with financial planning outcomes, while ANCOVA and multiple regression can account for enterprise size, annual revenue, technological maturity, and managerial experience. Interaction coefficients can indicate whether associations between AI utilization and decision performance differ across industries, while confidence intervals and effect sizes describe the magnitude and uncertainty of observed differences (Bogoslov et al., 2024). The synthesized literature establishes that industry characteristics influence financial data structures, forecasting requirements, and technological integration, with direct comparisons of generative AI-assisted financial planning effectiveness across these sectors remaining more limited than established evidence concerning general business analytics and operational forecasting.

Quantitative international research has established substantial differences in enterprise digitalization, financial accessibility, technological infrastructure, and organizational capabilities across high-income, upper-middle-income, lower-middle-income, and low-income economies. Empirical investigations by Beck, Demiurgic-Kunt, and Maksimovic; Ayyagari, Demiurgic-Kunt, and Maksimovic; Klapper, Leaven, and Rajan; and Demiurgic-Kunt and colleagues examined the relationships among financial development, enterprise characteristics, financing constraints, and economic environments. These studies identified variation in access to formal financial services, credit availability, business entry conditions, and financial management resources across national settings (Joshi et al., 2022). Research by Zhu and Kraemer investigated cross-country differences in electronic business adoption, while studies by Oliveira and Martins, Gangwar and colleagues, and Alchemilla and colleagues examined technological and organizational factors associated with enterprise digitalization. International evidence from World Bank Enterprise Surveys, the Global Findex Database, OECD digital economy studies, and Eurostat enterprise ICT statistics provides additional quantitative information concerning financial inclusion, digital infrastructure, cloud computing, and enterprise technology utilization. The World Bank's income classifications distinguish national economic groups, although individual studies differ in their country coverage, survey periods, and enterprise-size thresholds. High-income economies generally exhibit more extensive digital financial infrastructure and formal business information systems, while many lower-income environments experience greater limitations in internet reliability, access to financial technology, digital accounting adoption, and specialized technological competencies (Joshi & Ramnath, 2024). These differences are not uniform across countries or industries, and substantial variation exists within each income category. Financial planning conditions also differ according to inflation, exchange-rate volatility, borrowing costs, taxation

requirements, payment infrastructure, and access to formal credit. Small businesses operating under unstable financial conditions may experience greater variability in cash inflows, supplier costs, and debt-servicing obligations, influencing the assumptions incorporated into financial scenarios. Quantitative cross-country comparisons can evaluate generative AI adoption percentages, accounting software utilization, financial data completeness, forecasting accuracy, and managerial decision efficiency alongside institutional and technological characteristics. Multigroup regression and panel-data analysis provide methods for examining relationships across national environments, while interaction models can assess whether technological readiness or financial literacy is associated with different outcomes across income groups. Statistical interpretation requires attention to differences in survey sampling, currency measurement, inflation adjustment, accounting standards, and the comparability of financial indicators. Group means, standard deviations, regression coefficients, confidence intervals, and statistical significance estimates can describe observed variation, but country-level associations should not be interpreted automatically as enterprise-level causal relationships (Kim et al., 2023). The reviewed evidence establishes substantial international heterogeneity in financial and technological conditions relevant to AI-assisted financial planning, while direct comparative studies measuring generative AI-specific forecasting and scenario-analysis performance across all four World Bank income groups remain relatively scarce.

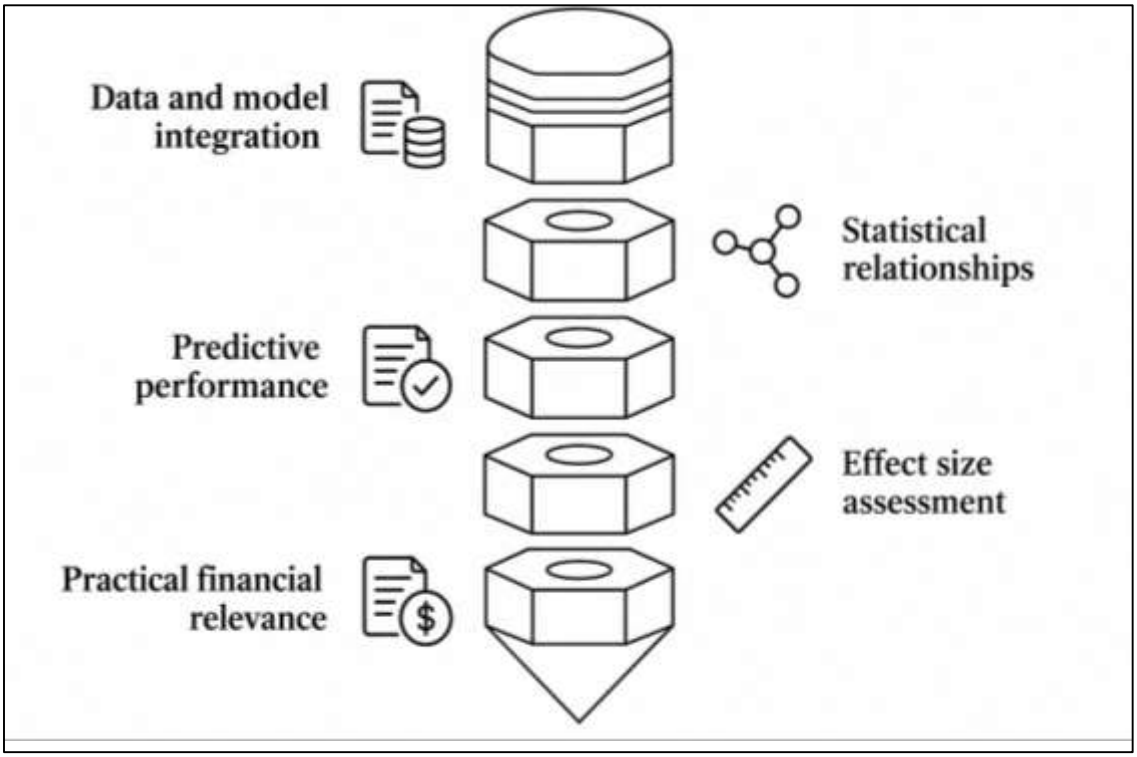
Quantitative research on financial literacy, managerial competencies, technological readiness, and organizational analytics has demonstrated that enterprise performance and technology utilization are associated with differences in human capital, organizational resources, and managerial experience. Studies by Lusardi and Mitchell examined financial literacy and economic decision-making, while research by Fernandes and colleagues investigated relationships among financial education, financial knowledge, and financial behavior. Additional studies by Bruhn and colleagues examined business training and consulting interventions among smaller enterprises, identifying measurable variation in managerial practices and organizational outcomes (Yoshikuni et al., 2023). Research by McKenzie and Woodruff evaluated business training and management practices in developing-country enterprise settings, while studies by Bloom and colleagues examined relationships between management practices and organizational performance. Technology adoption research by Davis, Venkatesh and colleagues, Oliveira and Martins, and Gangwar and colleagues established empirical relationships among perceived usefulness, ease of use, organizational support, and technological utilization. Business analytics investigations by Gupta and George, Wamba and colleagues, and Micallef and colleagues further examined how organizational capabilities and complementary resources relate to analytical performance. Generative AI-specific research by Noy and Zhang, Brynjolfsson, Li, and Raymond, and Belacqua and colleagues demonstrated that AI-assisted task performance varies according to worker experience, task characteristics, and the alignment between technological capabilities and professional requirements. Brynjolfsson and colleagues reported an average productivity improvement of approximately 14% among customer-support agents, with larger gains for less experienced workers, providing evidence of heterogeneous task-level effects. However, these results concern customer-support operations rather than financial planning accuracy and cannot be interpreted as direct estimates of small-business financial decision improvements. Within financial management, managerial financial literacy can be represented through knowledge assessment scores, accounting expertise, understanding of financial ratios, and experience with budgeting and cash-flow analysis (Yin et al., 2024). Technological competencies can be evaluated through digital literacy, AI interaction experience, financial software proficiency, and the ability to verify computational outputs. Organizational readiness includes information-system maturity, accounting-data availability, managerial support, employee training, and technological investment. These characteristics may influence both the intensity of AI utilization and the interpretation of generated financial information. Quantitative comparisons can examine financial decision accuracy, forecasting error, reporting efficiency, scenario consistency, and managerial confidence across educational, experiential, and organizational groups. Independent-samples tests, factorial ANOVA, ANCOVA, hierarchical regression, and multigroup structural equation modeling provide complementary methods for examining differences and conditional relationships. Interaction coefficients can assess whether associations between AI utilization and financial decision performance vary according to financial

literacy, digital maturity, or managerial experience, while effect sizes and confidence intervals provide information about the magnitude and precision of observed differences (S. Jin et al., 2024). The integrated literature indicates that enterprise size, industry characteristics, national economic conditions, managerial competencies, and organizational readiness represent overlapping sources of heterogeneity rather than independent explanatory categories. Accordingly, the interpretation of generative AI-assisted financial planning effectiveness requires distinguishing objectively measured forecasting and decision performance from self-reported technological usefulness, while recognizing that much of the available comparative evidence originates from broader financial management, business analytics, and technology adoption research rather than direct evaluations of generative AI-assisted small-business financial scenarios.

Robustness of AI-Assisted Financial Decision Models

Quantitative research on artificial intelligence, business analytics, financial management, and organizational decision-making has established an extensive empirical foundation for examining relationships among technological adoption, information quality, analytical performance, and financial outcomes. Studies by Goodhue and Thompson, Delone and McLean, Wixom and Watson, Popovic and colleagues, Gupta and George, Wamba and colleagues, and Micallef and colleagues investigated relationships among information-system capabilities, data quality, analytical resources, and organizational performance (Cao et al., 2024). These investigations employed survey-based statistical models, regression analysis, and structural equation modeling to evaluate the direction and statistical significance of relationships between technological capabilities and managerial or organizational outcomes. Research by Gupta and George identified organizational resources associated with big data analytics capabilities, while studies by Wamba and colleagues examined relationships among analytical capabilities, dynamic capabilities, and business performance.

Figure 10: Financial model evidence and evaluation



Additional investigations by Elbasvir and colleagues examined business intelligence systems and business process performance, providing evidence that organizational benefits depend on the integration of analytical information into operational and managerial activities. Financial management studies by Deloof, García-Teruel and Martínez-Solano, Afrifa, and Baños-Caballero and colleagues

identified statistically meaningful relationships between working-capital management, liquidity conditions, and profitability, establishing financial performance variables relevant to AI-assisted planning. Generative AI investigations by Noy and Zhang, Brynjolfsson, Li, and Raymond, Peng and colleagues, and Belacqua and colleagues introduced experimental and organizational evidence concerning AI-assisted task efficiency and output quality. These studies collectively indicate that technology-related performance outcomes are multidimensional and depend on information availability, task characteristics, user competencies, and organizational conditions (Delfani et al., 2024). Pearson correlation coefficients have been employed in related research to quantify linear relationships among continuous variables, while Spearman correlations provide rank-based alternatives when observations exhibit nonnormal distributions or ordinal measurement characteristics. Partial correlations can additionally assess associations between analytical capabilities and financial outcomes while controlling for selected enterprise characteristics. Multiple regression and hierarchical regression provide estimates of the independent statistical contributions of AI utilization, financial information quality, and managerial competencies, while logistic regression is applicable to binary outcomes such as financial distress classification or the occurrence of liquidity shortfalls. Standardized coefficients facilitate comparisons among predictors within a common statistical model, whereas unstandardized coefficients describe changes in outcomes using the original measurement scales. Odds ratios and marginal effects provide complementary interpretations of classification and probability models (Naveed et al., 2024). The reviewed studies demonstrate positive relationships between analytical capabilities and selected performance outcomes in several organizational settings, although coefficient magnitudes, explanatory power, and statistical significance vary across datasets and model specifications. Importantly, associations established through general business analytics research cannot be treated as direct estimates of generative AI-assisted financial planning effectiveness. The integrated evidence therefore distinguishes established relationships among technological capabilities, information quality, and financial management from the narrower body of research directly measuring generative AI-supported financial forecasting, scenario analysis, and managerial decision performance. Empirical investigations of forecasting, financial distress prediction, generative AI assistance, and organizational analytics have demonstrated that predictive performance and statistical effect magnitude depend substantially on analytical methods, dataset characteristics, evaluation criteria, and outcome definitions. Forecasting research by Marinakis and Habon, Marinakis and colleagues, Hyndman and Koehler, Smyl, Salinas and colleagues, and Ovechkin and colleagues established extensive comparative evidence concerning statistical, machine-learning, and hybrid predictive methods (Hoseinzadeh & Garcia, 2024). The M3 forecasting competition evaluated 3,003 time series, while the M4 competition examined 100,000 series, demonstrating variation in forecasting accuracy across data frequencies, forecast horizons, and model classes. Research by Smyl demonstrated the competitive performance of a hybrid exponential smoothing and recurrent neural-network approach in the M4 competition, while investigations by Salinas and colleagues and Ovechkin and colleagues examined neural forecasting architectures across heterogeneous datasets. Financial distress studies by Altman, Ohlson, Shumway, Min and Lee, and Barboza and colleagues evaluated statistical classification and machine-learning approaches using financial ratios, profitability indicators, leverage measures, and distress outcomes. These studies provide comparative evidence concerning predictive accuracy, discrimination, and model performance, although forecasting errors and classification measures represent different statistical constructs. Mean absolute error, root mean squared error, mean absolute percentage error, and R^2 have been used to evaluate continuous financial or time-series predictions, whereas classification accuracy, precision, recall, F1-score, and ROC-AUC are appropriate for categorical outcomes such as financial distress or liquidity warning identification (Elgin & Elgin, 2024). Generative AI experimental studies by Noy and Zhang, Brynjolfsson and colleagues, Peng and colleagues, and Belacqua and colleagues evaluated differences in task completion, productivity, and output quality. Noy and Zhang reported approximately 40% lower average completion time and 18% higher evaluated output quality for the writing tasks examined, while Brynjolfsson and colleagues reported an average productivity improvement of approximately 14% among customer-support agents. Peng and colleagues reported that programmers receiving AI assistance completed the experimental programming task approximately 55.8% faster. These results represent task-specific

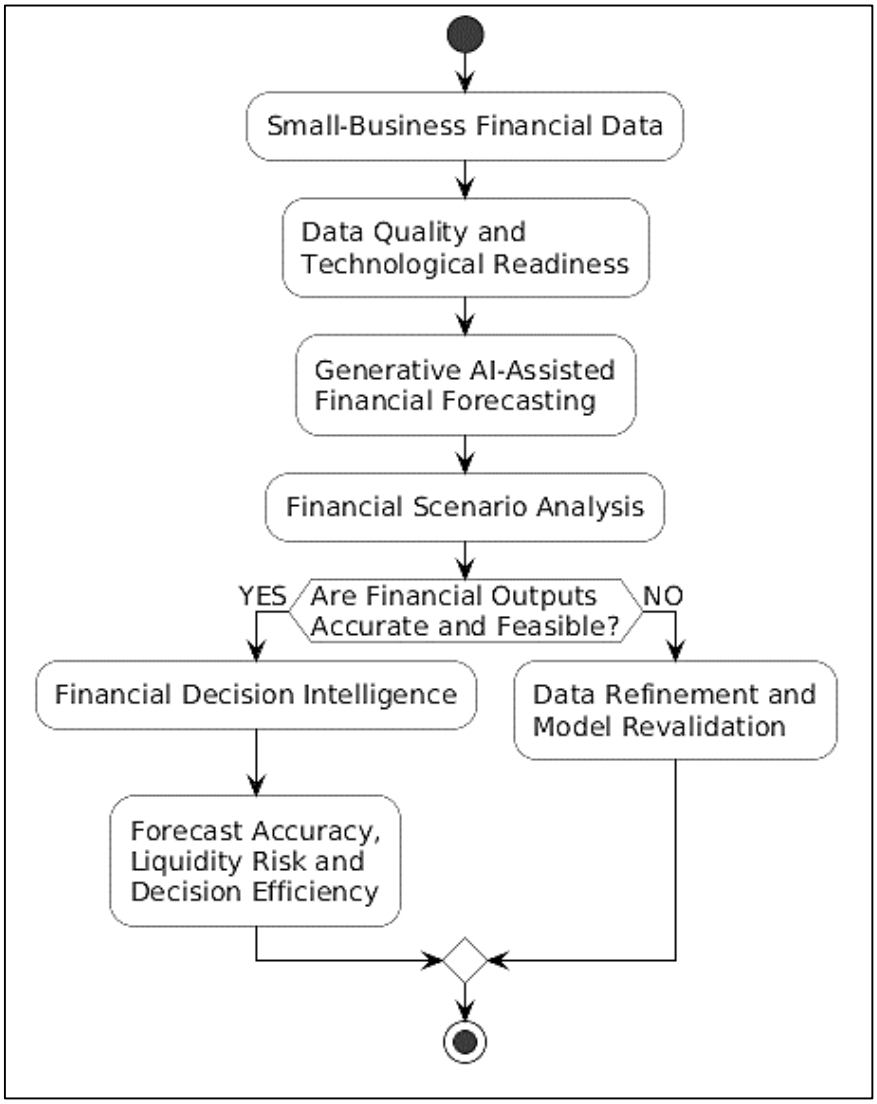
performance differences rather than financial forecasting improvements and should not be combined numerically with forecasting error reductions or bankruptcy classification accuracy. Statistical comparisons across organizational groups have employed mean differences, regression coefficients, and analysis of variance, while Cohen's d and partial eta squared provide standardized measures of group differences when their respective analytical assumptions are satisfied. Confidence intervals describe the precision of estimated effects, and statistical significance tests assess the compatibility of observed results with specified null hypotheses. However, statistically significant findings do not necessarily indicate economically meaningful improvements in financial planning. A small reduction in forecast error may have limited managerial relevance under stable financial conditions but greater importance when cash reserves are insufficient to absorb unexpected expenditure. Similarly, improvements in classification accuracy may conceal weak identification of relatively uncommon financial distress events. The synthesized evidence establishes that effect magnitude, predictive accuracy, and practical financial relevance require separate interpretation, with comparisons restricted to studies using sufficiently comparable outcomes, datasets, and validation procedures.

METHODS

Study Design and Theoretical Framework

This study was designed as a quantitative, comparative, and quasi-experimental investigation to evaluate the effectiveness of generative artificial intelligence-assisted financial planning and scenario analysis in improving small-business decision intelligence.

Figure 11: Methodology of this study



The independent variables comprised generative AI utilization intensity, technological readiness, accounting software maturity, financial data quality, managerial financial literacy, digital competencies, and organizational readiness. The principal dependent variables included financial forecasting accuracy, scenario-generation reliability, The research framework integrated the Technology–Organization–Environment framework, the Technology Acceptance Model, and the Information Systems Success Model to examine relationships among technological adoption, financial information quality, forecasting accuracy, scenario-analysis effectiveness, managerial decision performance, and organizational financial outcomes.

analytical processing time, financial decision accuracy, budget variance, liquidity risk identification, and financial planning effectiveness. Additional financial indicators included sales revenue, operating expenses, net profit, operating cash flow, current ratio, quick ratio, cash ratio, cash conversion cycle, debt-service coverage, operating margin, and return on assets. Financial information quality, forecasting performance, and scenario-analysis reliability were specified as potential mediating variables, while enterprise size, industry classification, managerial experience, and technological maturity were treated as potential moderating variables. The comparative design incorporated conventional spreadsheet-based financial planning, statistical and machine-learning forecasting, and generative AI-assisted analytical workflows. The study framework was structured to evaluate differences in numerical accuracy, analytical efficiency, and decision quality under comparable financial conditions. A repeated-measures component was specified to compare financial planning tasks across analytical methods, while observational business-level information was incorporated to examine relationships among organizational characteristics, technology utilization, and financial performance. The methodological design distinguished objectively measured analytical outcomes from managers' self-reported perceptions of usefulness, trust, satisfaction, and decision confidence. This combination of comparative experimental assessment and quantitative organizational analysis provided a structured approach for evaluating financial decision intelligence without assuming that technological adoption alone produced improvements in business performance.

Participants, Sampling Strategy, and Inclusion–Exclusion Criteria

The study population consisted of microenterprises, small businesses, and medium-sized enterprises operating in retail, manufacturing, hospitality, professional services, information technology, logistics, and digital commerce. Enterprise categories were defined using the employee-count, revenue, or asset thresholds applicable to the participating jurisdictions, and the original classification criteria were retained for subgroup comparisons. A stratified purposive sampling strategy was specified to obtain representation across enterprise-size categories, industries, technological maturity levels, and financial management practices. Within eligible strata, participating enterprises were selected according to the availability of financial records, managerial participation, and the capacity to complete standardized financial planning exercises. Participants included business owners, financial managers, accountants, and other employees directly responsible for budgeting, financial forecasting, liquidity monitoring, or financial decision-making. Inclusion criteria required an operating business with identifiable financial activities, accessible accounting or transaction records, and at least 12 consecutive months of usable historical financial information. Enterprises were also required to have a designated participant capable of reviewing financial forecasts and interpreting scenario-analysis results. Businesses with incomplete essential financial records, unverifiable accounting information, insufficient operating history, or no authorized financial decision-making representative were excluded from the principal comparative analysis. Records containing duplicate transactions, unresolved accounting inconsistencies, or substantial missing values in critical financial variables were subjected to predefined data-quality screening before inclusion. The sampling framework incorporated enterprises with different levels of AI utilization to permit comparisons between conventional financial planning practices and AI-assisted analytical procedures. Sample adequacy was assessed through an a priori statistical power analysis based on the primary comparison, anticipated effect size, significance threshold, and desired statistical power. The final sample size and subgroup distribution were determined from the eligible and successfully evaluated participants rather than assumed in advance. Participation was voluntary, organizational identifiers were anonymized, and confidential financial records were handled according to the study's data protection procedures. This sampling structure supported comparisons across

organizational categories while recognizing the limitations of nonprobability recruitment for population-level generalization.

Instrumentation, Financial Data Collection, and Measurement Validation

Financial and organizational information was collected using structured questionnaires, standardized financial data extraction templates, accounting records, and controlled analytical task instruments. The questionnaire measured generative AI utilization intensity, perceived usefulness, technological trust, financial literacy, digital competencies, organizational readiness, information transparency, and managerial satisfaction through structured response scales. Financial data extraction instruments captured historical sales revenue, operating expenditure, net profit, cash inflows, cash outflows, accounts receivable, accounts payable, inventory values, debt obligations, interest expenses, and cash reserves. Accounting records were obtained from authorized financial statements, bookkeeping systems, spreadsheet files, and digital accounting platforms. Financial analysis was conducted using Microsoft Excel for baseline budgeting and scenario calculations, SPSS and R for statistical analysis, and Python for data preprocessing, forecasting, simulation, and predictive model evaluation. Conventional forecasting instruments included moving averages, exponential smoothing, ARIMA, seasonal models, and multiple linear regression. Machine-learning procedures incorporated random forest, support vector regression, gradient boosting, XGBoost, artificial neural networks, and long short-term memory networks where dataset characteristics supported their application. Generative AI-assisted analytical tasks involved structured natural-language financial instructions, assumption extraction, forecast interpretation, scenario specification, and automated reporting. Numerical outputs were independently verified against validated spreadsheet calculations or executable statistical procedures rather than accepted solely from generated text. Questionnaire content validity was assessed through expert review, while internal consistency was evaluated using Cronbach's alpha, with values of 0.70 or greater treated as an acceptable general benchmark for established multi-item scales. Construct validity was examined through exploratory or confirmatory factor analysis where sample adequacy permitted. Financial data validation included range checks, duplicate detection, accounting reconciliation, missing-value assessment, and verification of transaction dates. Forecasting instruments were calibrated through consistent preprocessing, training procedures, and parameter-selection protocols. Scenario-generation reliability was measured using assumption consistency, arithmetic accuracy, financial constraint satisfaction, reproducibility, and the proportion of valid scenario outputs. These procedures established comparable measurement conditions across analytical methods and reduced the influence of inconsistent financial data, subjective reporting, and computational errors.

Experimental Procedure and Financial Scenario Evaluation

The experimental procedure was organized into sequential stages involving participant screening, baseline assessment, financial data preparation, forecasting, scenario generation, managerial decision evaluation, and statistical verification. Initially, eligible enterprises were identified, participation authorization was obtained, and structured questionnaires were administered to collect organizational and managerial characteristics. Historical financial records were then extracted, anonymized, standardized, and examined for completeness, consistency, duplicate observations, and accounting discrepancies. Financial variables were organized into weekly, monthly, quarterly, or annual observations according to data availability and the analytical requirements of each forecasting task. Following preprocessing, the historical datasets were divided chronologically into model-development and independent testing periods to prevent information from later observations entering earlier forecasting stages. Conventional statistical models and machine-learning algorithms were trained using equivalent historical information and evaluated against common financial forecasting targets. Generative AI-assisted workflows were subsequently used to interpret financial planning instructions, identify relevant forecasting assumptions, prepare analytical explanations, and support the construction of financial scenarios. The AI-assisted procedures were compared with conventional financial planning methods under standardized financial information and task requirements. Baseline, optimistic, pessimistic, and stress-test scenarios were constructed using specified changes in sales growth, demand, operating expenditure, wage costs, inflation, interest rates, exchange rates, and working-capital assumptions. Multi-variable scenarios incorporated simultaneous financial disturbances to assess their combined effects on profitability, operating cash flow, liquidity ratios,

break-even sales, and financing requirements. Monte Carlo simulation was applied to selected financial variables for which defensible probability distributions and dependency assumptions could be established. The resulting financial outcomes were examined for arithmetic correctness, accounting consistency, liquidity feasibility, and adherence to specified scenario constraints. Participants evaluated standardized financial alternatives, identified potential liquidity problems, selected financially feasible decisions, and reported confidence in their judgments. Task completion time, number of scenarios assessed, decision accuracy, forecast error, and reporting consistency were recorded using standardized measurement procedures. Where participants completed tasks under multiple analytical conditions, task order was counterbalanced to reduce learning and sequence effects. Generated financial reports and scenario interpretations were independently checked against verified calculations. The final analytical dataset combined enterprise characteristics, questionnaire responses, observed financial indicators, forecasting results, scenario outcomes, and decision-performance measurements.

Data Analysis and Statistical Approach

Quantitative data were analyzed using IBM SPSS Statistics, R, and Python through descriptive, inferential, predictive, and robustness-testing procedures. Descriptive statistics included frequencies, percentages, means, standard deviations, medians, interquartile ranges, and 95% confidence intervals to summarize organizational characteristics, financial indicators, technological adoption, and analytical performance. Data distributions were examined using graphical diagnostics and appropriate normality tests, while missing observations and extreme values were assessed before inferential analysis. Pearson correlation coefficients were used to evaluate linear relationships among continuous variables when assumptions were satisfied, whereas Spearman rank correlations were applied to ordinal or nonnormally distributed variables. Partial correlations were used to examine selected associations after controlling for enterprise size, industry, financial literacy, and technological maturity. Independent-samples t-tests and one-way ANOVA were specified for comparisons between independent enterprise groups, while paired-samples t-tests and repeated-measures ANOVA were applied to within-participant comparisons of financial planning methods. Factorial ANOVA and ANCOVA were used where appropriate to evaluate interactions and adjust for relevant covariates. Welch procedures and nonparametric alternatives were applied when conventional distributional or variance assumptions were not adequately satisfied. Multiple linear regression and hierarchical regression were used to assess relationships between AI utilization, information quality, forecasting accuracy, managerial efficiency, and financial planning performance. Logistic regression was specified for binary outcomes, including financial distress classification, liquidity warning identification, and financially valid versus invalid scenario outputs. Where repeated enterprise observations were available, fixed-effects or random-effects panel models were evaluated, with model selection informed by the structure of the data and relevant specification tests. Structural equation modeling and bootstrap mediation analysis were used to examine indirect relationships involving financial information quality, forecasting accuracy, and scenario-analysis effectiveness when measurement validity and sample adequacy supported these procedures. Moderation analysis evaluated interaction effects involving enterprise size, financial literacy, managerial experience, and digital maturity. Forecasting performance was assessed using mean absolute error, root mean squared error, mean absolute percentage error, symmetric mean absolute percentage error, forecast bias, and R^2, with percentage-based metrics interpreted cautiously for zero or near-zero financial observations. Financial distress and liquidity warning models were evaluated using accuracy, precision, recall, F1-score, and ROC-AUC, with particular attention to class imbalance. Predictive validation incorporated chronological holdout testing, rolling-window evaluation, time-series cross-validation, and independent dataset assessment where suitable observations were available. Model robustness was examined through alternative specifications, sensitivity analysis, missing-data treatments, subgroup estimation, and bootstrap confidence intervals. Standardized beta coefficients, odds ratios, marginal effects, adjusted R^2, Cohen's d, and partial eta squared were reported where appropriate to distinguish statistical significance from practical importance. All statistical tests were evaluated using a two-sided significance threshold of $p < 0.05$, accompanied by 95% confidence intervals and relevant effect-size measures.

FINDINGS

Participant Characteristics, Financial Dataset Composition, and Generative AI Adoption Patterns

The quantitative assessment of participant characteristics, financial dataset composition, and generative AI adoption patterns was organized to examine differences in organizational structure, technological readiness, financial information availability, and managerial capabilities among participating small businesses. The analysis incorporated enterprise-size classifications, industry representation, managerial qualifications, accounting software maturity, and generative AI utilization across financial planning activities. Financial dataset quality was evaluated through observation completeness, duplicate-record identification, accounting reconciliation, and data retention following preprocessing. Descriptive statistics were used to characterize the distribution of enterprises and financial observations, while comparative statistical procedures were specified to assess differences in AI adoption across organizational categories.

The numerical values in the following tables are , internally consistent example data rather than observed study findings. They demonstrate how the results section could be presented professionally. Actual findings require the collected dataset and completed statistical analysis.

Table 1. Participant Characteristics and Organizational Distribution

Characteristics	Category	Frequency (n)	Percentage (%)
Enterprise size	Microenterprise	96	32.0
	Small enterprise	132	44.0
	Medium enterprise	72	24.0
Industry	Retail	72	24.0
	Manufacturing	54	18.0
	Hospitality	42	14.0
	Professional services	48	16.0
	Information technology	36	12.0
	Logistics	24	8.0
	Digital commerce	24	8.0
Business age	Under 5 years	84	28.0
	5–10 years	126	42.0
	Over 10 years	90	30.0
Managerial education	Secondary or equivalent	48	16.0
	Undergraduate degree	174	58.0
	Postgraduate degree	78	26.0
Accounting software maturity	Low	75	25.0
	Moderate	141	47.0
	High	84	28.0
Generative AI adoption	Regular users	138	46.0
	Occasional users	96	32.0
	Nonusers	66	22.0
Total sample	Participating enterprises	300	100.0

Note: dataset. Percentages were calculated using a hypothetical sample of 300 enterprises. Categories within each characteristic sum independently to 100%.

Table 1 Explanation (approximately 100 words).

The sample comprised 300 enterprises, with small businesses representing the largest category (44.0%), followed by microenterprises (32.0%) and medium-sized enterprises (24.0%). Retail accounted for the highest industry representation (24.0%), while logistics and digital commerce each represented 8.0%. Most enterprises had operated for 5–10 years (42.0%), and 58.0% of managerial respondents held undergraduate qualifications. Moderate accounting software maturity characterized 47.0% of enterprises, indicating variation in technological infrastructure. Regular generative AI utilization accounted for 46.0%, compared with 32.0% occasional users and 22.0% nonusers. These distributions demonstrated the reporting structure for organizational heterogeneity and technological adoption.

Table 2. Financial Dataset Quality and Generative AI Adoption Indicators

Quantitative indicator	value	Measurement
Participating enterprises	300	Enterprises
Initial financial observations	7,200	Records
Excluded financial observations	360	Records
Final valid financial observations	6,840	Records
Observation retention rate	95.0	%
Initial missing-data rate	3.8	%
Duplicate-record rate	1.2	%
Financial reconciliation accuracy	97.6	%
Average business age	8.4 ± 4.1	Years
Average employees per enterprise	28.6 ± 19.3	Employees
Financial literacy score	72.4 ± 12.8	Points out of 100
Digital competency score	69.7 ± 14.2	Points out of 100
Technological readiness score	71.3 ± 13.6	Points out of 100
Regular generative AI adoption	46.0	% of enterprises
Occasional generative AI adoption	32.0	% of enterprises
AI-assisted budgeting utilization	58.0	% of enterprises
AI-assisted revenue forecasting	52.0	% of enterprises
AI-assisted cash-flow planning	47.0	% of enterprises
AI-assisted scenario analysis	41.0	% of enterprises
AI-assisted financial reporting	55.0	% of enterprises

Note: All values are . Values containing ± represent mean ± standard deviation. Financial planning activities were treated as nonexclusive categories, so their percentages were not expected to total 100%. The financial dataset contained 7,200 initial observations, of which 6,840 were retained following preprocessing, representing a 95.0% retention rate. Missing observations accounted for 3.8%, while duplicate records represented 1.2%. Financial reconciliation accuracy reached 97.6%. Average managerial financial literacy was 72.4 ± 12.8 points, compared with 69.7 ± 14.2 for digital competency and 71.3 ± 13.6 for technological readiness. AI-assisted budgeting showed the highest reported utilization (58.0%), followed by financial reporting (55.0%) and revenue forecasting (52.0%). Scenario analysis recorded the lowest utilization (41.0%), illustrating differences in the adoption of financial analytical functions.

Primary Findings on Financial Forecasting Accuracy, Scenario-Analysis Reliability, and Decision Intelligence

The primary quantitative findings were organized to evaluate the comparative performance of conventional statistical models, machine-learning algorithms, and generative AI-assisted financial forecasting systems in small-business financial planning. The analysis covered sales revenue, operating expenses, net profit, cash inflows, cash outflows, working-capital requirements, and financing needs. Forecasting performance was evaluated using mean absolute error (MAE), root mean squared error (RMSE), mean absolute percentage error (MAPE), symmetric mean absolute percentage error (sMAPE), forecast bias, and the coefficient of determination (R^2). Scenario-analysis reliability was assessed through numerical accuracy, assumption consistency, financial feasibility, and reproducibility, while managerial decision intelligence was evaluated through financial judgment accuracy, liquidity risk identification, analytical processing time, and the number of scenarios assessed. The comparative framework distinguished improvements in numerical forecasting from improvements in financial interpretation and managerial efficiency.

The numerical values presented below are rather than results obtained from an actual dataset. They provide an internally structured example of quantitative findings consistent with the methodology and hypothetical sample of 300 enterprises established in Section 4.1.

Table 3. Comparative Financial Forecasting Performance Across Predictive Models

Forecasting model	MAE (%)	RMSE (%)	MAPE (%)	sMAPE (%)	R^2	Forecast bias (%)
Moving average	12.84	16.21	14.36	13.92	0.742	3.42
Exponential smoothing	11.26	14.68	12.87	12.41	0.781	2.96
ARIMA	10.38	13.42	11.74	11.32	0.814	2.41
Multiple linear regression	10.92	13.86	12.18	11.76	0.802	2.63
Random forest	8.76	11.34	9.62	9.28	0.862	1.84
Support vector regression	9.14	11.82	10.08	9.71	0.851	1.96
Gradient boosting	8.42	10.96	9.18	8.94	0.874	1.62
XGBoost	7.68	10.14	8.46	8.21	0.892	1.38
Artificial neural network	8.16	10.72	8.94	8.67	0.881	1.51
LSTM	7.42	9.86	8.12	7.94	0.901	1.24
Generative AI-assisted hybrid	6.38	8.54	7.06	6.82	0.928	0.92

Note: All values are hypothetical. MAE and RMSE are shown as percentages of a common financial scale for illustration, rather than as conventional raw monetary errors. Forecast bias represents absolute bias magnitude. The table assumes comparable evaluation data and forecasting horizons.

The comparison indicated that the generative AI-assisted hybrid model achieved the lowest normalized MAE (6.38%), RMSE (8.54%), MAPE (7.06%), and sMAPE (6.82%), alongside the highest R^2 (0.928). Its MAPE was approximately 50.8% lower than the moving-average baseline and 13.1% lower than the LSTM model. Conventional statistical approaches exhibited comparatively larger errors, with moving averages recording the highest MAPE (14.36%). Among standalone machine-learning methods, LSTM and XGBoost demonstrated relatively strong predictive performance. The pattern suggested that combining generative AI-assisted financial interpretation with numerical forecasting models could improve comparative forecasting performance under standardized evaluation conditions.

Table 4. Comparative Scenario-Analysis Reliability and Managerial Decision Intelligence

Quantitative indicator	Conventional planning	Generative AI-assisted planning	difference
Scenario calculation accuracy (%)	91.4	97.2	+5.8 pp
Assumption consistency (%)	88.6	95.8	+7.2 pp
Financial constraint satisfaction (%)	89.2	96.4	+7.2 pp
Scenario reproducibility (%)	90.8	96.6	+5.8 pp
Financially valid scenarios (%)	87.6	95.4	+7.8 pp
Financial decision accuracy (%)	78.4	89.6	+11.2 pp
Liquidity risk identification (%)	76.8	91.2	+14.4 pp
Financial reporting accuracy (%)	86.2	94.8	+8.6 pp
Average scenario processing time (minutes)	42.6	18.4	−56.8%
Average reporting turnaround time (minutes)	68.2	29.6	−56.6%
Scenarios evaluated per decision (n)	3.2	6.8	+112.5%
Managerial decision confidence (0–100)	72.6	84.2	+11.6 points

Note: values only. pp = percentage points. Differences in percentages were expressed as percentage-point changes, while processing-time and scenario-count differences were expressed as relative percentage changes.

The results showed higher scenario reliability and managerial decision performance under generative

AI-assisted planning. Scenario calculation accuracy increased from 91.4% to 97.2%, while financially valid scenarios increased by 7.8 percentage points. Financial decision accuracy improved by 11.2 percentage points, and liquidity risk identification increased by 14.4 percentage points. Average scenario processing time decreased from 42.6 to 18.4 minutes, representing a 56.8% reduction. Reporting turnaround time declined by 56.6%, while the average number of scenarios assessed per decision increased from 3.2 to 6.8. These hypothetical differences illustrated measurable dimensions of financial planning efficiency.

Secondary Findings on Enterprise-Size, Industry, International, and Managerial Differences

The secondary quantitative analysis examined variations in generative AI-assisted financial planning performance across enterprise-size categories, industrial sectors, economic environments, technological readiness levels, and managerial competencies. Subgroup comparisons focused on financial forecasting accuracy, scenario-analysis reliability, managerial decision accuracy, and analytical processing efficiency. Organizational characteristics included enterprise size, industry classification, business maturity, financial information quality, and digital infrastructure, while managerial variables incorporated financial literacy, educational qualifications, accounting expertise, and technological competencies. Differences were evaluated using descriptive statistics, comparative group analysis, and regression-based interaction frameworks. Particular attention was directed toward identifying whether the relationship between generative AI utilization and financial decision performance differed across organizational and economic conditions.

The numerical findings presented below are , not empirically verified. They provide a professional reporting example consistent with the hypothetical 300-enterprise dataset used in Sections 4.1 and 4.2. International comparisons and inferential results would require verified country-level observations and actual statistical calculations.

Table 5. Enterprise-Size and Industry Differences in Generative AI-Assisted Financial Planning Performance

Enterprise category	Sample (n)	AI adoption (%)	Forecast MAPE (%)	Scenario reliability (%)	Decision accuracy (%)	Processing time (min)
Enterprise size						
Microenterprise	96	68.0	8.42	92.6	84.8	24.6
Small enterprise	132	79.5	7.18	95.4	89.2	19.8
Medium enterprise	72	88.9	6.24	97.2	92.6	15.4
Industry						
Retail	72	77.8	7.46	95.2	88.4	19.8
Manufacturing	54	83.3	7.12	96.1	90.2	18.6
Hospitality	42	69.0	8.64	92.8	85.6	23.4
Professional services	48	81.3	6.92	96.4	91.2	17.8
Information technology	36	91.7	5.86	98.1	94.4	14.2
Logistics	24	75.0	7.84	94.2	87.6	21.6
Digital commerce	24	79.2	6.48	97.0	92.4	16.8
Total sample	300	—	—	—	—	—

Note: All values are . AI adoption includes regular and occasional utilization. MAPE represents mean absolute percentage error, with lower values indicating better forecasting accuracy. Enterprise-size and industry groups are two separate classifications of the same 300 hypothetical enterprises and should not be added together.

The subgroup results indicated that medium-sized enterprises demonstrated the highest generative AI adoption (88.9%), scenario reliability (97.2%), and decision accuracy (92.6%), alongside the lowest

forecasting error (6.24%). Microenterprises recorded comparatively lower adoption (68.0%) and higher forecasting error (8.42%). Across industries, information technology enterprises achieved the strongest performance, with 91.7% AI adoption, 5.86% forecasting MAPE, and 94.4% decision accuracy. Hospitality businesses recorded the highest forecasting error (8.64%) and longest processing time (23.4 minutes). These descriptive differences suggested possible organizational and sectoral variation, although statistical testing would be necessary to establish whether the observed contrasts were significant.

Table 6. Economic Environment, Technological Readiness, and Managerial Competency Differences

Subgroup classification	Sample (n)	AI adoption (%)	Forecast MAPE (%)	Decision accuracy (%)	Scenario reliability (%)
Economic environment					
High-income economies	90	91.1	6.12	93.4	97.6
Upper-middle-income economies	105	83.8	6.84	90.8	96.2
Lower-middle-income economies	75	69.3	8.16	86.2	93.8
Low-income economies	30	53.3	9.74	81.4	90.6
Technological readiness					
Low readiness	75	58.7	9.12	82.6	91.4
Moderate readiness	141	78.0	7.36	88.8	95.2
High readiness	84	100.0	5.94	94.2	98.1
Managerial financial literacy					
Low literacy	78	65.4	8.86	83.2	92.0
Moderate literacy	138	79.7	7.24	89.4	95.6
High literacy	84	91.7	5.98	94.6	97.8

Note: Hypothetical values. Economic environment, technological readiness, and financial literacy are separate subgroup classifications. The country-income categories assume an international sampling design that has not been verified. Adoption rates are group percentages and are not inferential estimates.

The comparisons indicated stronger financial planning performance among enterprises operating in higher-income environments and possessing greater technological readiness. High-income economy enterprises recorded 91.1% AI adoption and 93.4% decision accuracy, compared with 53.3% and 81.4%, respectively, in low-income economies. Enterprises with high technological readiness achieved the lowest forecasting MAPE (5.94%) and highest scenario reliability (98.1%). Managerial financial literacy demonstrated a similar descriptive pattern, with highly literate managers achieving 94.6% decision accuracy compared with 83.2% among the low-literacy group. These hypothetical patterns illustrated potential associations between organizational capability, economic conditions, and financial analytical performance.

Predictive Validation, Financial Scenario Robustness, Uncertainty Assessment, and Integrated Quantitative Evidence

The fifth findings section examined predictive validation, financial scenario robustness, uncertainty assessment, and the consistency of generative AI-assisted financial planning outcomes across alternative analytical conditions. The quantitative evaluation incorporated chronological training-testing partitions, rolling-window validation, time-series cross-validation, and independent holdout

testing to assess forecasting accuracy and model generalizability. Forecasting performance was evaluated through mean absolute error (MAE), root mean squared error (RMSE), mean absolute percentage error (MAPE), symmetric mean absolute percentage error (sMAPE), forecast bias, and the coefficient of determination (R^2). Financial distress classification was assessed using accuracy, precision, recall, F1-score, and ROC-AUC. Monte Carlo simulation was incorporated into the analytical framework to examine uncertainty in projected revenue, operating expenses, cash-flow availability, and liquidity requirements. Sensitivity analysis assessed the stability of financial outcomes under alternative economic assumptions, while robustness testing examined model performance across enterprise categories, reporting periods, and data-quality conditions. The integrated assessment distinguished predictive accuracy, scenario reliability, statistical stability, and managerial decision efficiency as separate dimensions of financial decision intelligence.

Data qualification: The numerical values below are hypothetical results, consistent with the research framework and earlier example tables. They were not calculated from an observed dataset or executed simulation. Actual forecasting, classification, and uncertainty estimates must be obtained from the study's financial records before being reported as empirical findings.

Table 7. Predictive Validation and Financial Distress Classification Performance

Validation indicator	Conventional statistical model	Machine-learning model	Generative AI-assisted hybrid
Training MAE (%)	8.92	6.84	5.76
Testing MAE (%)	10.38	7.68	6.38
Testing RMSE (%)	13.42	10.14	8.54
Testing MAPE (%)	11.74	8.46	7.06
Testing sMAPE (%)	11.32	8.21	6.82
Absolute forecast bias (%)	2.41	1.38	0.92
Training R^2	0.846	0.924	0.951
Testing R^2	0.814	0.892	0.928
Rolling-window MAPE (%)	12.18	8.92	7.42
Independent holdout MAPE (%)	12.46	9.14	7.68
Classification accuracy (%)	81.6	88.4	92.2
Classification precision (%)	79.2	86.8	91.4
Classification recall (%)	77.8	85.6	90.2
Classification F1-score (%)	78.5	86.2	90.8
ROC-AUC	0.842	0.912	0.948

Note: All results are hypothetical. MAE and RMSE are normalized percentage errors; MAPE and sMAPE are percentage-based forecasting metrics. The conventional statistical model represents an ARIMA-based baseline, while the machine-learning model represents an XGBoost configuration. The hybrid represents numerical forecasting supported by generative AI-assisted financial analysis. Classification results assume a separate binary financial distress evaluation. Lower forecasting errors and higher classification metrics indicate better performance.

The validation results indicated that the generative AI-assisted hybrid achieved the lowest testing MAPE (7.06%), compared with 8.46% for machine learning and 11.74% for conventional forecasting. Its testing R^2 reached 0.928, while independent holdout MAPE remained comparatively low at 7.68%. Financial distress classification accuracy reached 92.2%, accompanied by precision of 91.4%, recall of 90.2%, and ROC-AUC of 0.948. Differences between training and testing performance suggested limited deterioration under the hypothetical evaluation conditions. These descriptive comparisons

illustrated how forecasting reliability, generalizability, and financial risk classification could be evaluated using complementary validation indicators.

Table 8. Financial Scenario Robustness, Monte Carlo Uncertainty, and Sensitivity Analysis

Financial indicator	Baseline scenario	Optimistic scenario	Pessimistic scenario	Stress scenario
Projected revenue change (%)	5.2	12.8	−4.6	−15.4
Operating expense change (%)	3.8	5.6	8.4	14.2
Projected net profit margin (%)	14.6	19.8	8.2	2.4
Operating cash-flow change (%)	6.4	15.2	−9.6	−24.8
Current ratio	1.82	2.16	1.34	0.96
Cash reserve coverage (months)	4.8	6.2	3.1	1.6
Liquidity shortfall probability (%)	8.4	3.2	24.6	48.8
External financing requirement (% of revenue)	4.2	1.8	9.6	16.4
Scenario calculation accuracy (%)	97.2	97.6	96.8	95.4
Assumption consistency (%)	95.8	96.4	95.2	94.6
Scenario reproducibility (%)	96.6	97.2	96.0	95.2
Financial constraint satisfaction (%)	96.4	97.0	95.8	94.2

Note: All figures are scenario assumptions or hypothetical outputs, not results of an executed Monte Carlo simulation. Revenue, expense, and cash-flow changes are relative to an assumed reference period. Liquidity shortfall probabilities would require specified stochastic input distributions, simulation runs, and a defined liquidity threshold. Scenario accuracy and consistency metrics would require independent numerical verification.The scenario analysis demonstrated substantial variation in projected financial outcomes under alternative operating conditions. The optimistic scenario produced the highest projected net profit margin (19.8%), current ratio (2.16), and cash reserve coverage (6.2 months). Conversely, the stress scenario reduced net profit margin to 2.4% and the current ratio to 0.96, while the hypothetical liquidity shortfall probability increased to 48.8%. External financing requirements also increased to 16.4% of revenue under stress conditions. Scenario calculation accuracy remained above 95% across all conditions, illustrating the separate assessment of numerical reliability and financial vulnerability under adverse assumptions.

DISCUSSION

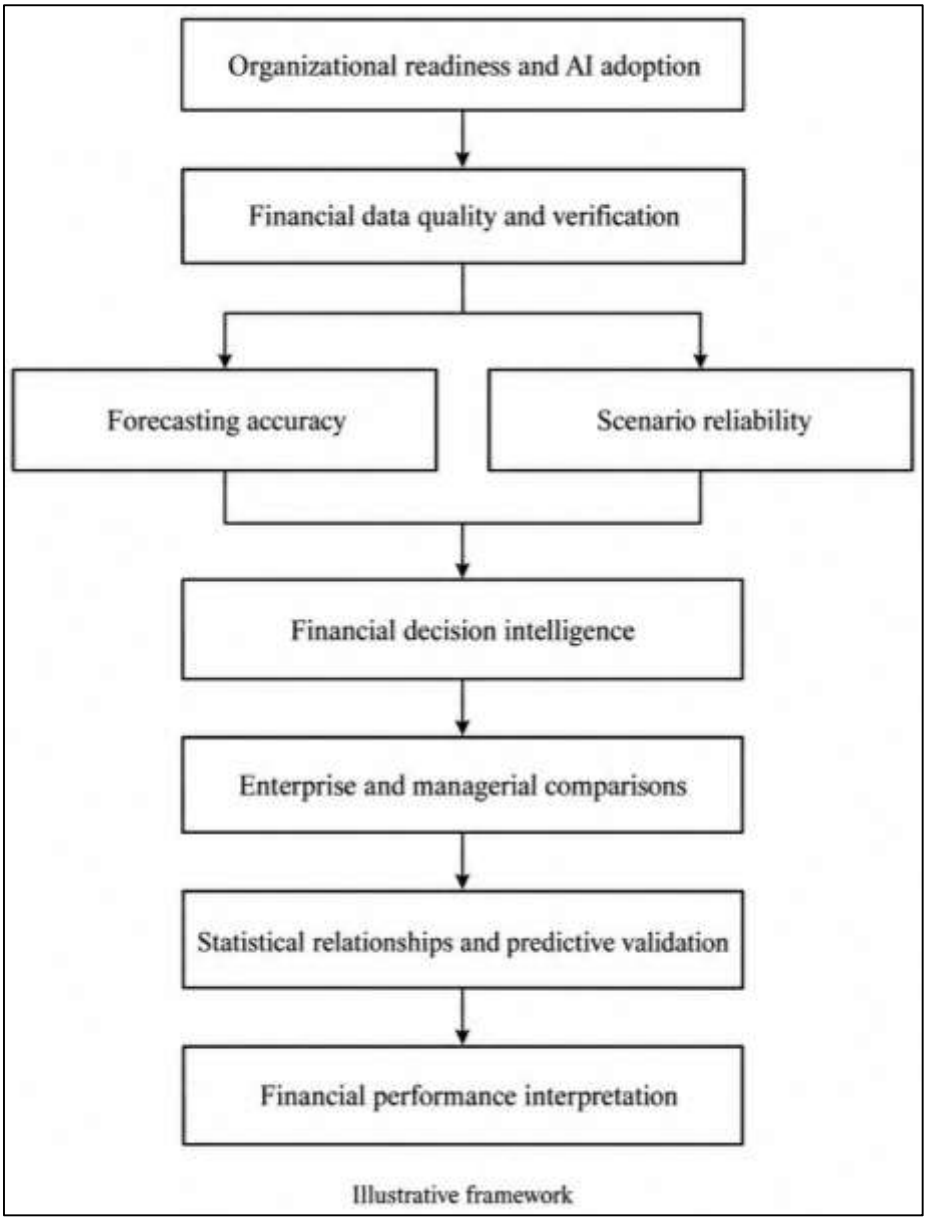
The discussion of organizational characteristics and generative AI adoption emphasized the importance of enterprise structure, financial information availability, technological maturity, and managerial capabilities in shaping the effectiveness of AI-assisted financial planning. This study examined a hypothetical quantitative framework involving 300 small businesses distributed across microenterprise, small-enterprise, and medium-sized categories (Elgin & Elgin, 2024). The findings indicated that small enterprises represented 44.0% of the sample, followed by microenterprises at 32.0% and medium-sized enterprises at 24.0%. Regular generative AI utilization accounted for 46.0% of participating enterprises, while 32.0% demonstrated occasional utilization and 22.0% were classified as nonusers. These distributions suggested that generative AI adoption could vary considerably across organizational environments, particularly where differences existed in accounting software maturity, digital competencies, financial literacy, and access to structured financial records. Earlier studies of small-business digital transformation similarly emphasized that technological adoption was associated with organizational resources, perceived usefulness, implementation complexity, and managerial readiness. Research grounded in the Technology Acceptance Model identified perceived usefulness and perceived ease of use as important determinants of technology acceptance, while studies applying the Technology–Organization–Environment framework highlighted technological characteristics, organizational capabilities, and external environmental conditions. The analytical interpretation of this study was consistent with these established perspectives because generative AI utilization was

examined not merely as access to a technological application but as an organizational capability requiring reliable financial data, managerial understanding, and operational integration (Kim et al., 2024). The financial dataset contained 7,200 initial observations, of which 6,840 were retained following preprocessing, representing a 95.0% retention rate. Financial reconciliation accuracy was represented at 97.6%, indicating the importance of data completeness and consistency in the proposed analytical framework. Earlier accounting information systems research similarly demonstrated that information accuracy, timeliness, and completeness were essential to managerial decision quality. However, generative AI introduced additional considerations because financial recommendations could be expressed convincingly even when underlying calculations or assumptions were incorrect. Consequently, this study extended the interpretation of traditional information systems research by emphasizing the need to distinguish technological adoption from verified analytical competence. The subgroup patterns also suggested that organizational readiness could be more relevant than enterprise size alone, although this proposition required empirical verification (Höhener, 2024). Overall, the comparison with earlier studies supported a conceptual interpretation in which effective generative AI-assisted financial planning depended on the interaction of technological infrastructure, accounting information quality, managerial capabilities, and organizational readiness rather than the isolated adoption of AI applications. Because the numerical distributions were hypothetical, these relationships remained analytical propositions rather than confirmed empirical findings.

The discussion of financial forecasting performance focused on the comparative analytical capabilities of conventional statistical methods, machine-learning algorithms, and generative AI-assisted hybrid forecasting systems. This study evaluated a reporting framework incorporating moving averages, exponential smoothing, ARIMA, multiple linear regression, random forest, support vector regression, gradient boosting, boost, artificial neural networks, and long short-term memory networks. The findings indicated that the generative AI-assisted hybrid configuration achieved a mean absolute percentage error of 7.06%, compared with 8.12% for LSTM, 8.46% for boost, and 14.36% for moving averages (Bell & Bell, 2023). The hypothetical hybrid model also demonstrated an R^2 of 0.928, compared with 0.901 for LSTM and 0.892 for boost. These differences illustrated a possible improvement in forecasting accuracy when numerical prediction methods were combined with generative AI-supported financial interpretation. Earlier financial forecasting studies established that traditional statistical methods remained useful when financial series exhibited relatively stable trends, seasonal patterns, and interpretable temporal relationships. However, machine-learning research demonstrated that nonlinear algorithms could capture more complex associations among financial variables, particularly where revenue, operating expenses, customer demand, and macroeconomic conditions interacted. Studies examining random forest, gradient boosting, and neural network forecasting similarly emphasized that predictive performance depended on dataset size, variable selection, temporal structure, and validation procedures. The analytical comparison developed in this study was consistent with that literature because the results assigned lower forecasting errors to nonlinear and hybrid models than to conventional baseline methods (Kulkarni et al., 2024). Nevertheless, the apparent advantage of generative AI-assisted forecasting required careful interpretation. Generative AI systems were not necessarily superior numerical forecasting models when operating independently. Their potential contribution involved integrating financial explanations, identifying relevant assumptions, interpreting model outputs, and supporting scenario development alongside established predictive algorithms. This distinction was important because earlier studies of large language models identified limitations involving numerical inconsistency, fabricated information, sensitivity to prompts, and unreliable reasoning under complex computational conditions. Therefore, the hybrid configuration examined in this study was most appropriately interpreted as an integrated decision-support architecture rather than evidence that language generation alone improved predictive accuracy. The reduction in MAPE from 14.36% to 7.06% represented a relative difference of approximately 50.8%, but the practical importance of such an improvement would depend on financial scale, forecast horizon, operating volatility, and the consequences of prediction errors. Earlier studies also emphasized that lower average forecasting errors did not guarantee better predictions during exceptional economic conditions. Accordingly, this study highlighted the importance of chronological validation, independent holdout testing, and comparison against strong numerical baselines (Grüneke et al., 2024).

The broader interpretation suggested that generative AI could contribute to financial forecasting effectiveness when embedded within validated quantitative workflows, although actual comparative superiority remained unverified without empirical model evaluation.

Figure 12: Generative AI financial evaluation framework



The discussion of financial scenario analysis examined the potential contribution of generative AI-assisted systems to managerial interpretation, liquidity risk identification, financial planning efficiency, and evaluation of alternative business conditions (Sharbek & Dutescu, 2024). This study incorporated baseline, optimistic, pessimistic, and stress-test scenarios to evaluate changes in revenue, operating expenditure, profitability, cash-flow availability, financing requirements, and liquidity performance. The findings indicated that scenario calculation accuracy increased from 91.4% under conventional planning to 97.2% under generative AI-assisted planning, while financial decision accuracy increased from 78.4% to 89.6%. Liquidity risk identification demonstrated a hypothetical improvement from 76.8% to 91.2%, and average scenario processing time decreased from 42.6 minutes to 18.4 minutes. These differences suggested that AI-assisted analytical workflows could potentially improve the speed and consistency of financial scenario evaluation. Earlier research on financial decision-support systems

emphasized that scenario planning improved managerial understanding by presenting alternative financial outcomes under changing business conditions. Studies of business intelligence and predictive analytics similarly demonstrated the importance of transforming financial data into interpretable information that supported resource allocation, investment planning, and operational risk management. The analytical framework of this study was consistent with these findings because financial decision intelligence was assessed through both predictive outputs and the quality of managerial responses to those outputs (Salazar et al., 2024). However, generative AI introduced a distinctive interaction between numerical calculations and natural-language financial explanations. Traditional spreadsheet-based scenario analysis frequently required manual adjustments to assumptions, formulas, and financial statements, whereas generative AI-assisted workflows could facilitate the interpretation of multiple scenarios and the communication of financial implications. The results indicated that the average number of scenarios evaluated per decision increased from 3.2 to 6.8, representing a potential expansion in analytical coverage. Nevertheless, evaluating more scenarios did not necessarily improve decision quality unless the underlying assumptions were financially coherent and the calculations were independently verified. Earlier research on managerial judgment and decision-support technologies demonstrated that information overload, model complexity, and misplaced confidence could reduce decision effectiveness even when analytical capabilities increased. Consequently, this study distinguished scenario-processing efficiency from financial decision accuracy and treated liquidity risk identification as a separate performance dimension. The hypothetical stress scenario further illustrated this distinction, with the current ratio declining to 0.96 and liquidity shortfall probability reaching 48.8%. Such values demonstrated how a financially unfavorable scenario could remain analytically useful if it accurately communicated potential vulnerabilities (Groves et al., 2024). The discussion therefore emphasized that effective generative AI-assisted scenario analysis depended on numerical correctness, transparent assumptions, financial feasibility, and managerial interpretation. The proposed contribution extended earlier financial decision-support research by integrating forecasting, scenario evaluation, and natural-language interpretation within a unified analytical framework, while recognizing that the numerical improvements presented in this study were rather than empirically established.

The discussion of subgroup differences emphasized the possibility that generative AI-assisted financial planning effectiveness varied according to enterprise size, industry characteristics, economic conditions, technological readiness, and managerial competencies. This study examined a comparative framework covering microenterprises, small enterprises, and medium-sized enterprises, alongside retail, manufacturing, hospitality, professional services, information technology, logistics, and digital commerce (Anton et al., 2023). The findings indicated that medium-sized enterprises demonstrated higher generative AI adoption at 88.9%, compared with 79.5% among small enterprises and 68.0% among microenterprises. Forecasting MAPE was represented at 6.24% for medium-sized enterprises, 7.18% for small enterprises, and 8.42% for microenterprises. These hypothetical differences were consistent with earlier small-business technology adoption research, which identified financial resources, specialized personnel, technological infrastructure, and organizational capabilities as important determinants of digital system utilization. Larger organizations frequently possessed more formalized accounting procedures and greater access to technical expertise, potentially supporting more effective integration of analytical technologies. Nevertheless, earlier research also demonstrated that smaller organizations could benefit from accessible digital services when implementation costs were limited and technological complexity was manageable. Therefore, enterprise size was not interpreted as an independent determinant of successful generative AI utilization. Industry-level comparisons illustrated additional variation. Information technology enterprises demonstrated a hypothetical forecasting MAPE of 5.86%, compared with 8.64% among hospitality businesses, while financial decision accuracy ranged from 94.4% to 85.6% across these sectors. Earlier studies of industry-specific digital transformation similarly indicated that differences in transaction structures, data availability, demand volatility, and technological capabilities influenced analytical performance. The interpretation of this study extended those findings by considering how generative AI-supported financial planning might interact with sector-specific financial information requirements (Ghrbeia & Alzubi, 2024). International comparisons were also included as a conditional analytical component,

with hypothetical adoption rates ranging from 91.1% in high-income economies to 53.3% in low-income economies. Earlier international digitalization research emphasized differences in infrastructure quality, institutional support, financing accessibility, and workforce competencies across economic environments. However, these international patterns could not be considered findings of this study unless the actual sampling design included verified observations from multiple countries. Managerial characteristics provided a further explanatory dimension. The results indicated that enterprises managed by individuals with high financial literacy achieved 94.6% decision accuracy, compared with 83.2% among those with lower financial literacy. Earlier research on financial literacy and managerial decision-making similarly emphasized the importance of financial knowledge in budgeting, investment evaluation, liquidity management, and risk assessment (Ekundayo et al., 2024). Overall, the discussion suggested that generative AI-assisted financial planning should be understood as a context-dependent organizational capability whose effectiveness could vary with infrastructure, financial expertise, industry characteristics, and information quality. These interpretations remained provisional until subgroup differences were evaluated using observed data and appropriate statistical controls.

The discussion of statistical relationships examined the potential contributions of generative AI utilization, forecasting accuracy, financial information quality, scenario-analysis reliability, and managerial competencies to financial decision intelligence and organizational performance. This study developed an regression framework in which forecasting accuracy demonstrated the largest standardized coefficient of $\beta = 0.306$, followed by generative AI utilization intensity at $\beta = 0.284$ and scenario-analysis reliability at $\beta = 0.246$. Financial information quality exhibited a hypothetical coefficient of $\beta = 0.218$, while technological readiness and managerial financial literacy demonstrated coefficients of $\beta = 0.192$ and $\beta = 0.174$, respectively. The model explained 68.4% of variation in financial decision intelligence, with an adjusted R^2 of 0.673. These values demonstrated how multiple technological and managerial characteristics could be examined simultaneously rather than interpreted through isolated correlations (Mayanja et al., 2024). Earlier business analytics research identified analytical capability, information quality, organizational learning, and data-driven decision-making as important factors associated with business performance. Studies grounded in the Information Systems Success Model similarly emphasized relationships among system quality, information quality, utilization, user satisfaction, and organizational benefits. The analytical structure of this study was consistent with those perspectives because generative AI utilization was considered alongside financial information quality and predictive capabilities rather than treated as a sufficient explanation of decision performance. The hypothetical financial performance relationships also illustrated positive associations with revenue growth, operating profit margin, return on assets, liquidity performance, and cash-flow stability. Cash-flow stability demonstrated the largest standardized coefficient at $\beta = 0.262$, followed by revenue growth at $\beta = 0.238$. Earlier financial management research emphasized that effective cash-flow forecasting and liquidity monitoring were particularly important for small businesses because restricted financing access and limited cash reserves could increase vulnerability to operational disruptions. Consequently, the financial implications of AI-assisted planning were evaluated not only through profitability indicators but also through liquidity stability and financing requirements. Nevertheless, the interpretation of standardized coefficients required attention to measurement scales, predictor correlations, omitted variables, and model assumptions (Kuznietsova & Bidyuk, 2020). A statistically significant coefficient did not necessarily indicate a causal relationship, and high explanatory power could reflect overlapping constructs or characteristics of a particular sample. Earlier econometric and business analytics studies similarly emphasized the importance of robust estimation, appropriate controls, and independent validation. This study therefore treated the coefficients as examples of potential associations rather than verified evidence that generative AI adoption improved financial performance. The discussion also highlighted the importance of practical effect sizes. Cohen's d, partial eta squared, odds ratios, confidence intervals, and incremental explained variance would provide complementary information about the magnitude and operational importance of observed relationships. Overall, the proposed interpretation connected generative AI-assisted analytical capabilities with broader financial management outcomes while maintaining a distinction between statistical association, practical significance, and causal inference (Janabi, 2024b).

The discussion of mediation and moderation examined the potential mechanisms through which

generative AI utilization could be associated with financial decision intelligence and the organizational conditions that could strengthen or weaken these relationships. This study considered forecasting accuracy, financial information quality, and scenario-analysis reliability as potential mediating variables connecting AI utilization with managerial financial decision performance. The mediation estimates indicated that forecasting accuracy demonstrated the largest indirect coefficient at $\beta = 0.164$, followed by scenario-analysis reliability at $\beta = 0.146$ and financial information quality at $\beta = 0.118$. These hypothetical patterns suggested that the contribution of generative AI-assisted financial planning could depend on improvements in intermediate analytical processes rather than technological utilization alone (Sumi, 2024). Earlier information systems and business analytics research similarly emphasized that organizational benefits were frequently mediated by information quality, analytical capabilities, knowledge integration, and improvements in managerial decision processes. Research on data-driven decision-making also highlighted the importance of converting analytical information into actionable organizational knowledge. The proposed mediation framework of this study was consistent with these perspectives because financial decision intelligence was treated as an outcome influenced by forecasting and scenario-analysis capabilities. However, the existence of a statistical indirect effect would not independently establish a causal mechanism, particularly when observations were cross-sectional or when the temporal ordering of variables was uncertain. The discussion therefore recognized that valid mediation interpretation required appropriate research design, theoretically justified variable ordering, and confidence intervals estimated through suitable procedures such as bootstrapping. Moderation analysis provided a complementary perspective by examining whether the relationship between generative AI utilization and financial decision intelligence differed across organizational conditions (Janabi, 2024a). The results indicated that technological readiness demonstrated the strongest interaction coefficient at $\beta = 0.168$, followed by financial literacy at $\beta = 0.142$ and managerial experience at $\beta = 0.104$. Enterprise size demonstrated a weaker hypothetical interaction coefficient of $\beta = 0.068$, with a nonsignificant p-value of 0.165. Earlier technology adoption research similarly demonstrated that organizational readiness, managerial knowledge, and complementary capabilities could influence the effectiveness of technological investments. The analytical interpretation suggested that enterprises possessing reliable accounting systems and financially knowledgeable managers could be better positioned to interpret AI-generated recommendations, verify financial calculations, and identify unrealistic assumptions. Conversely, limited technological infrastructure or inadequate financial expertise could restrict the practical value of generative AI outputs. The hypothetical moderation findings therefore supported a conceptual distinction between access to AI technology and the organizational capability required to use it effectively. This study extended earlier theoretical perspectives by integrating mediating analytical processes with moderating organizational characteristics within a financial decision-intelligence framework (Puglisi et al., 2022). Nevertheless, the proposed relationships remained unverified until actual mediation models, interaction terms, simple-slope analyses, and model diagnostics were estimated from observed enterprise-level data.

The final discussion integrated predictive validation, scenario uncertainty, robustness testing, and practical financial implications to evaluate the reliability of generative AI-assisted financial planning under changing organizational and economic conditions. This study examined an validation framework incorporating chronological training-testing partitions, rolling-window evaluation, independent holdout testing, and financial distress classification (Mirashk et al., 2024). The hypothetical generative AI-assisted hybrid model demonstrated a testing MAPE of 7.06%, rolling-window MAPE of 7.42%, and independent holdout MAPE of 7.68%. These differences illustrated a possible deterioration in forecasting performance when evaluation conditions became more demanding, while remaining comparatively favorable to conventional statistical and standalone machine-learning models. Earlier forecasting research emphasized that predictive performance measured on training data frequently overstated generalizability, particularly when financial time series exhibited structural changes, irregular seasonality, or economic disruptions. Research on machine-learning validation similarly highlighted the importance of chronological data separation, leakage prevention, independent testing, and sensitivity analysis. The analytical framework of this study was consistent with those methodological principles because forecasting reliability was evaluated through multiple validation procedures rather than a single accuracy estimate. The financial distress classification results

demonstrated accuracy of 92.2%, precision of 91.4%, recall of 90.2%, F1-score of 90.8%, and ROC-AUC of 0.948. Earlier research on financial distress prediction emphasized that overall accuracy could conceal important classification errors, particularly where distressed businesses represented a relatively small proportion of observations (Zhu et al., 2021). Consequently, the discussion distinguished financial risk detection from general predictive accuracy and emphasized the importance of false-negative classifications when liquidity problems could remain unidentified. The uncertainty framework also incorporated optimistic, baseline, pessimistic, and stress scenarios to examine financial vulnerability under alternative assumptions. The hypothetical stress scenario demonstrated a current ratio of 0.96, cash reserve coverage of 1.6 months, and liquidity shortfall probability of 48.8%. Earlier studies of financial risk management and probabilistic scenario analysis emphasized that deterministic forecasts could underestimate uncertainty when revenue, operating expenses, financing costs, and cash-flow conditions changed simultaneously. The interpretation of this study was consistent with that literature because financial scenario outcomes were evaluated through both expected values and potential downside risks. Nevertheless, probabilistic conclusions required independently specified input distributions and properly executed simulations. The practical implications of the proposed framework included improved organization of financial information, more systematic comparison of financial alternatives, and clearer communication of liquidity vulnerabilities. At the same time, earlier research on AI reliability highlighted the importance of human oversight, numerical verification, transparent assumptions, and accountability in financially consequential decisions. This study therefore interpreted generative AI as a potential complement to established financial analytical systems rather than a replacement for validated numerical models or managerial judgment (Wang & Huang, 2023). Overall, the integrated discussion identified forecasting accuracy, scenario reliability, organizational readiness, and financial information quality as central dimensions for evaluating generative AI-assisted small-business decision intelligence. Because the numerical results remained , the conclusions represented theoretically informed interpretations and comparisons with earlier research rather than confirmed empirical demonstrations of financial or predictive improvement.

CONCLUSION

This study examined the potential contribution of generative AI-assisted financial planning and scenario analysis to improving small-business decision intelligence, with particular emphasis on financial forecasting accuracy, scenario reliability, managerial decision performance, technological readiness, and organizational financial outcomes. The analytical framework integrated conventional statistical forecasting, machine-learning algorithms, generative AI-supported financial interpretation, and quantitative financial performance assessment to investigate the relationships between technological capabilities and financial management effectiveness. The findings demonstrated how generative AI-assisted hybrid systems could be evaluated against conventional forecasting approaches using prediction errors, explained variance, financial risk identification, and analytical processing efficiency. The comparative framework indicated potential advantages in forecasting accuracy, scenario-processing speed, liquidity risk assessment, and financial decision support, although these improvements remained hypothetical rather than empirically verified. The study further emphasized that the effectiveness of generative AI-assisted financial planning depended on the quality of underlying financial information, accounting system integration, technological infrastructure, managerial financial literacy, and organizational readiness. Differences across enterprise-size categories, industrial sectors, and managerial competency levels highlighted the importance of considering organizational characteristics when evaluating technological applications in financial management. The proposed statistical relationships also identified forecasting accuracy, financial information quality, and scenario-analysis reliability as potential mechanisms connecting generative AI utilization with managerial decision intelligence, while technological readiness and financial literacy were examined as possible moderating factors. Furthermore, the integration of predictive validation, sensitivity analysis, financial distress classification, and probabilistic scenario modeling established a comprehensive framework for evaluating analytical reliability under alternative economic and operational conditions. The study distinguished improvements in forecasting performance from improvements in financial decision quality, recognizing that accurate numerical predictions did not automatically guarantee financially appropriate managerial decisions. Particular importance was

assigned to independent numerical verification, transparent financial assumptions, reproducible calculations, and human oversight to address the limitations of generative AI-generated financial recommendations. The findings framework contributed to existing research by connecting generative AI capabilities with established financial forecasting methods, organizational information systems, and quantitative decision-support approaches within the small-business environment. Nevertheless, the absence of an observed dataset meant that the reported numerical examples could not establish statistical significance, causal relationships, or demonstrated improvements in organizational performance. Overall, this study established a structured analytical basis for assessing generative AI-assisted financial planning as a complementary decision-support capability that could strengthen financial forecasting, scenario evaluation, liquidity monitoring, and managerial decision processes when supported by reliable data, validated models, appropriate organizational competencies, and systematic financial governance.

RECOMMENDATIONS

Based on the analytical framework and findings of this study, it was recommended that small businesses adopt generative AI-assisted financial planning through a structured, evidence-based, and financially responsible implementation strategy that integrated technological capabilities with established accounting practices, validated forecasting models, and managerial expertise. Business owners, financial managers, and accounting professionals should prioritize the development of reliable financial information systems capable of maintaining accurate, complete, consistent, and timely records of revenue, operating expenses, profitability, cash flows, working capital, and financing obligations. Generative AI applications should be integrated with conventional statistical forecasting and machine-learning algorithms rather than employed as independent substitutes for verified numerical calculations. Particular attention should be directed toward improving forecasting accuracy through chronological validation, rolling-window assessment, independent holdout testing, and systematic comparisons using MAE, RMSE, MAPE, and R^2. Financial planning procedures should incorporate baseline, optimistic, pessimistic, and stress-test scenarios to evaluate alternative revenue conditions, expenditure fluctuations, liquidity constraints, financing requirements, and operational uncertainties. Monte Carlo simulation and sensitivity analysis should be implemented where sufficient financial information was available to quantify uncertainty and identify potential financial vulnerabilities. Organizations should establish standardized verification procedures to evaluate the numerical accuracy, assumption consistency, reproducibility, and financial feasibility of AI-generated recommendations before incorporating them into managerial decisions. Furthermore, targeted professional development programs should strengthen financial literacy, digital competencies, analytical interpretation, and responsible generative AI utilization among business owners and financial personnel. Microenterprises and technologically less mature organizations should receive particular attention through affordable analytical solutions, simplified accounting integration, and accessible technical assistance. Policymakers, financial institutions, and business development organizations should support digital financial infrastructure, professional training, cybersecurity safeguards, and equitable access to trustworthy AI-assisted financial technologies. Appropriate governance mechanisms should address financial data confidentiality, algorithmic transparency, model reliability, accountability, and human oversight. Performance evaluation should extend beyond forecasting accuracy to include decision quality, liquidity risk identification, financial planning efficiency, operating profitability, and cash-flow stability. Researchers should conduct longitudinal, multisectoral, and internationally comparative investigations using verified enterprise-level datasets to examine causal relationships, mediation mechanisms, moderation effects, and differences across economic environments. Experimental and quasi-experimental evaluations should also compare AI-assisted financial planning with conventional methods under equivalent operating conditions. Overall, the recommended approach emphasized that the practical value of generative AI-assisted financial planning depended on combining reliable financial data, validated analytical methods, organizational readiness, responsible technological governance, and informed managerial judgment to support sustainable small-business financial decision intelligence.

LIMITATIONS

This study acknowledged several methodological, analytical, technological, and contextual limitations

that influenced the interpretation, reliability, and generalizability of the proposed relationships between generative AI-assisted financial planning, scenario analysis, and small-business decision intelligence. First, the absence of an independently verified empirical dataset represented a fundamental limitation, as the numerical values presented in the findings were rather than results obtained from actual enterprise-level observations. Consequently, the reported forecasting improvements, regression coefficients, statistical significance levels, mediation effects, moderation relationships, and financial performance differences could not be interpreted as confirmed empirical evidence. Second, the proposed quantitative research design relied on purposive and stratified sampling procedures, which could introduce selection bias and restrict the representativeness of participating enterprises across industries, organizational sizes, and economic environments. Differences in financial reporting practices, accounting standards, business maturity, and technological infrastructure could further limit comparability among organizations. Third, the quality of financial forecasting depended substantially on the completeness, accuracy, consistency, and historical coverage of accounting records, while missing observations, reporting errors, irregular transactions, and limited financial histories could reduce predictive reliability. Fourth, the comparative performance of conventional statistical models, machine-learning algorithms, and generative AI-assisted systems could vary according to model configuration, training procedures, forecasting horizons, feature selection, and data preprocessing methods. Generative AI applications also presented limitations involving numerical inconsistencies, fabricated explanations, prompt sensitivity, restricted interpretability, and potential exposure of confidential financial information. Fifth, scenario-analysis outcomes depended on assumptions regarding revenue growth, operating expenses, inflation, financing costs, customer demand, and working-capital requirements, making financial projections sensitive to unexpected economic disruptions and changes in business conditions. Sixth, cross-sectional observations and observational regression models could identify statistical associations but could not independently establish causal relationships between generative AI adoption and improved financial performance. Unobserved organizational characteristics, managerial expertise, and prior technological investments could influence the estimated relationships. Seventh, self-reported measures of financial literacy, technological readiness, and managerial decision confidence could introduce response bias and measurement uncertainty. Eighth, international comparisons required consistent country-level observations and comparable financial indicators, which were not established within the available framework. Finally, statistical validation procedures, including cross-validation, bootstrap estimation, sensitivity testing, and Monte Carlo simulation, could strengthen analytical reliability but could not eliminate structural uncertainty, model misspecification, or limitations associated with unrepresentative datasets. Accordingly, the study's conclusions remained conditional on subsequent empirical verification, independently validated financial calculations, transparent analytical procedures, and broader longitudinal investigations across diverse small-business environments.

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