



Artificial Intelligence-Augmented ERP Systems: A Systematic Review of Predictive Analytics Integration for Real-Time Financial Decision-Making

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Abstract

Artificial Intelligence (AI), together with emerging digital technologies, is increasingly transforming Enterprise Resource Planning (ERP) systems by reshaping organizational operations, decision-making processes, and strategic planning. The rapid adoption of AI within enterprise information systems has generated substantial scholarly interest in AI-enabled ERP environments. Nevertheless, a more comprehensive and systematic understanding of this evolving research domain remains necessary. This study conducts a systematic literature review of academic and grey literature, following the PRISMA 2020 framework, to examine the integration of three major categories of AI technologies – generative AI, analytics AI, and automation AI – within business organizations, with particular emphasis on predictive analytics for real-time financial decision-making. The review traces the development of AI-ERP research, identifies emerging trends, and highlights important research gaps and future directions. Existing bibliometric evidence provides important context for this synthesis: analyzing 183 academic publications and 35 industry documents, Hurbean et al. (2026) report an annual growth rate of approximately 11.3% in AI-ERP research, with automation-related studies accounting for roughly 41% of the literature, positive impacts reported in approximately 93% of reviewed studies, and ethical or governance-related issues addressed in fewer than 2%. The present review extends this evidence base through a thematic rather than bibliometric synthesis; record counts for the database search underpinning this review are reported in the Methodology section rather than in this abstract. Overall, the findings identify automation, predictive analytics, and generative AI as the principal research themes, while trust, governance, explainability, and long-term strategic implications remain insufficiently explored. The evidence suggests that AI is fundamentally extending conventional ERP systems by introducing greater autonomy, adaptability, predictive intelligence, and intelligent process capabilities into integrated enterprise environments. These developments have important implications for enterprise information-systems research and practice, particularly by demonstrating how AI-enabled ERP systems can strengthen organizational processes, facilitate timely and data-driven decision-making, and improve operational and strategic performance.

Keywords

Artificial Intelligence; Enterprise Resource Planning (ERP); Predictive Analytics; Real-Time Financial Decision-Making; Machine Learning.

INTRODUCTION

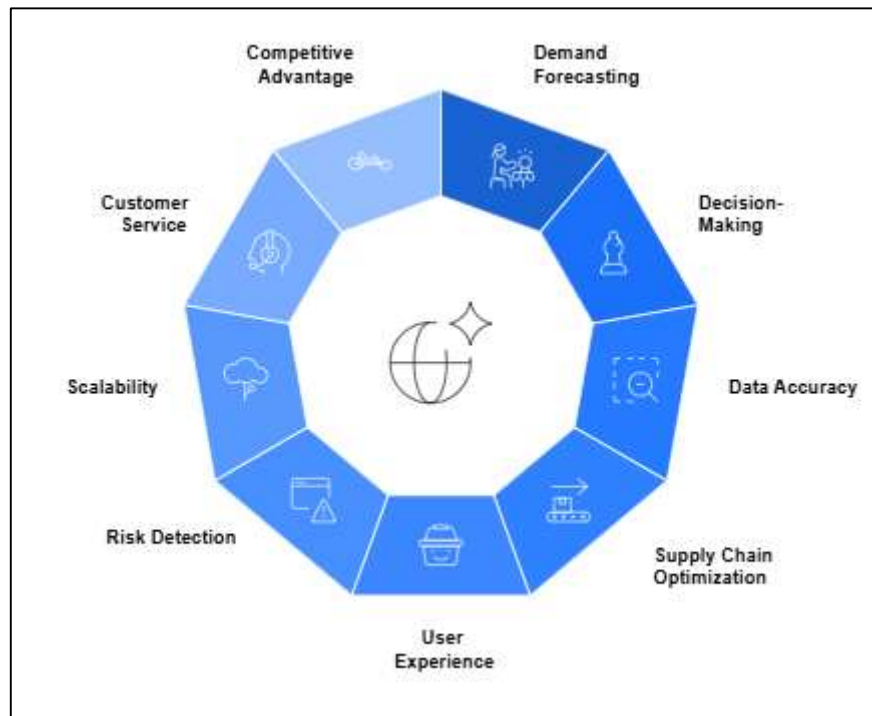
Artificial Intelligence (AI) is transforming Enterprise Resource Planning (ERP) systems from traditional transaction-processing platforms into intelligent, predictive, and increasingly autonomous decision-support environments. AI contributes to ERP by analyzing large volumes of integrated organizational data, identifying complex patterns, predicting future outcomes, detecting anomalies, and generating actionable recommendations, enabling organizations to move from reactive decision-making based on historical reports toward proactive and data-driven management. One of the most significant contributions of AI is predictive analytics, which enables ERP systems to forecast future business and financial conditions using machine-learning and deep-learning techniques. Unlike conventional ERP systems that primarily provide historical reports and dashboards, AI-enabled ERP systems can analyze sales, accounts receivable, accounts payable, inventory, procurement, expenditure, and cash-flow data to predict revenue, liquidity requirements, expenses, demand, and financial risks. This predictive capability enables managers to identify potential problems before they become critical and take preventive action. AI also strengthens real-time financial decision-making by continuously processing ERP transactions and updating predictions as new information becomes available, allowing managers to receive timely alerts concerning unusual transactions, declining cash balances, payment delays, unexpected expenditures, and changes in customer or supplier behavior. Another important contribution is risk and anomaly detection, through which machine-learning algorithms can identify unusual transaction patterns associated with potential fraud, duplicate payments, credit risks, abnormal expenses, or supplier risks.

AI further improves business-process automation by supporting activities such as invoice classification, document processing, account reconciliation, expense categorization, payment processing, and financial data validation, thereby reducing manual effort, processing time, and human error while allowing employees to focus on more strategic activities. The integration of AI also enhances forecasting and resource optimization because ERP systems contain interconnected information relating to customers, suppliers, inventory, procurement, production, sales, employees, and financial activities. By analyzing these datasets simultaneously, AI can improve demand forecasting, inventory planning, procurement, workforce allocation, working-capital management, and budget planning. Furthermore, combining internal ERP information with external data, such as economic indicators, market conditions, exchange rates, and customer trends, can strengthen the accuracy and relevance of predictive models. Emerging generative and conversational AI technologies are also expanding ERP capabilities by enabling users to interact with enterprise systems through natural-language queries, automatically summarize financial information, generate reports, explain financial trends, and obtain context-specific recommendations without requiring advanced technical knowledge. Explainable AI is particularly important in financial ERP applications because decision-makers need to understand the factors underlying AI-generated predictions and recommendations. Transparent explanations can improve user trust and support responsible decision-making when AI outputs influence credit assessment, financial risk, compliance, or resource allocation. In addition, AI enables ERP systems to support continuous organizational learning by incorporating new transaction data and decision outcomes into ongoing model evaluation and improvement. Consequently, the traditional ERP sequence of transaction, database, report, and managerial interpretation can evolve into a closed-loop process of transaction, integrated data, AI analysis, prediction, recommendation, decision, action, and feedback.

However, realizing these benefits requires high-quality data, effective system integration, appropriate AI expertise, cybersecurity, governance, organizational readiness, and human oversight. Issues such as data privacy, algorithmic bias, model drift, explainability, accountability, and security must therefore be addressed alongside technological implementation. Overall, AI expands ERP capabilities by integrating automation, predictive intelligence, real-time analytics, and decision support within a unified enterprise environment. Its contribution is particularly significant for financial management

because it transforms continuously generated ERP data into timely forecasts, risk insights, and actionable recommendations, providing organizations with greater opportunities for proactive financial planning, improved risk management, faster decision-making, and enhanced organizational performance.

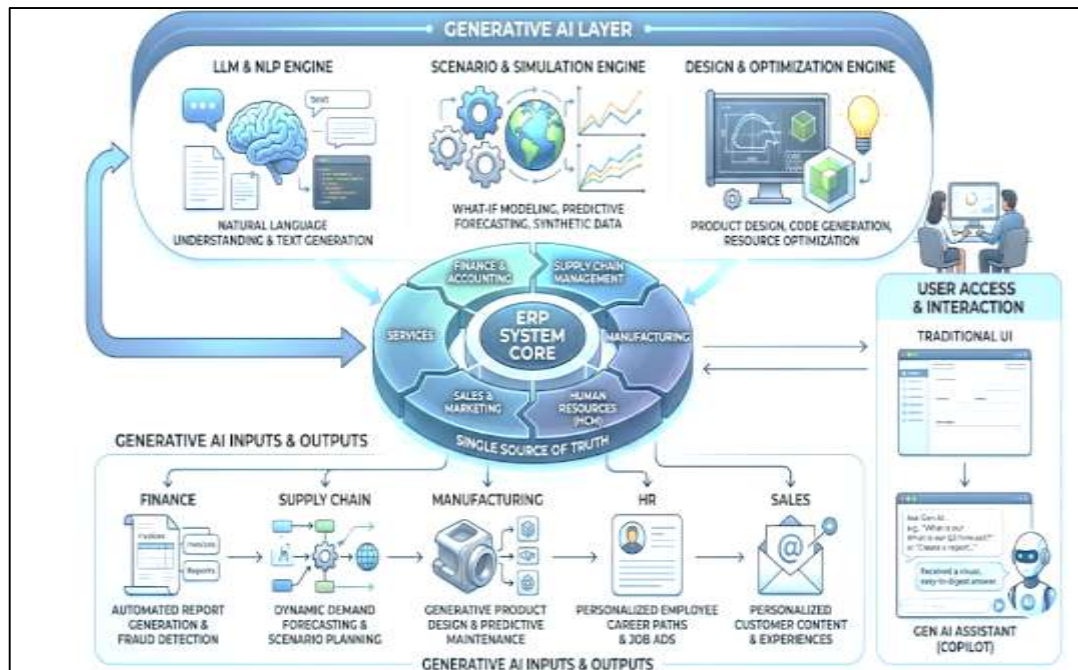
Figure 1: AI Contribution in ERP Systems



In the context of AI adoption in organizations, three primary areas of focus can be identified: generative AI, automation, and analytical AI. These three dimensions represent complementary capabilities through which AI can reshape organizational processes, information management, operational efficiency, and managerial decision-making. Generative AI focuses on producing new content and knowledge from existing information and can support activities such as natural-language interaction, document generation, report preparation, knowledge retrieval, scenario development, and intelligent communication. Within ERP environments, generative AI can provide conversational access to enterprise data, summarize financial and operational information, generate management reports, and assist employees in interpreting complex business information. AI-based automation focuses on using intelligent technologies to perform repetitive, structured, and time-consuming organizational activities with limited human intervention. When combined with robotic process automation, natural-language processing, computer vision, and intelligent workflow technologies, AI automation can support invoice processing, payment reconciliation, transaction classification, procurement activities, inventory management, payroll processing, and other routine ERP functions. This can reduce manual workloads, processing delays, operational costs, and human errors while allowing employees to devote greater attention to strategic and analytical responsibilities. Analytical AI, meanwhile, focuses on extracting meaningful patterns, relationships, and predictions from large volumes of organizational data using machine learning, deep learning, statistical modeling, and advanced analytical techniques. In ERP systems, analytical AI can be applied to revenue forecasting, cash-flow prediction, demand forecasting, financial-risk assessment, fraud and anomaly detection, credit-risk prediction, inventory optimization, expense forecasting, and performance analysis. Of these three areas, analytical AI is particularly relevant to predictive ERP because it enables organizations to move beyond retrospective reporting toward forward-looking intelligence. By continuously analyzing historical and real-time ERP data,

analytical AI can identify emerging trends, estimate future outcomes, and provide early warnings about potential operational or financial problems. The integration of these three AI capabilities can therefore create a more comprehensive intelligent ERP environment in which generative AI supports human interaction and knowledge work, automation AI improves process execution, and analytical AI supports prediction and decision intelligence.

Figure 2: Generative AI Contributions In ERP Systems



Their combined application can enable ERP systems to evolve from systems that primarily record and report organizational activities into intelligent platforms capable of interpreting information, predicting future conditions, recommending actions, and, in selected circumstances, executing predefined decisions. This transformation is particularly important for financial management because organizations increasingly require timely and reliable information regarding cash flow, revenue, expenditure, liquidity, credit risk, and financial performance. By integrating predictive analytics with real-time ERP data, organizations can strengthen financial planning, improve risk identification, accelerate decision-making, and respond more effectively to changing business conditions. However, the successful adoption of these AI capabilities also depends on data quality, system interoperability, organizational readiness, employee AI competencies, cybersecurity, explainability, governance, and appropriate human oversight. Therefore, the three dimensions of AI adoption should be considered not merely as separate technological applications but as interconnected capabilities that collectively contribute to the development of intelligent, adaptive, predictive, and increasingly autonomous ERP systems. Generative Artificial Intelligence (GenAI) represents a significant evolution in AI technology through the development of foundation models capable of generating new forms of content from learned patterns and contextual instructions (Schneider, 2024). Unlike conventional AI systems that primarily classify information, recognize patterns, or make predictions, GenAI can generate text, images, audio, video, code, and other forms of digital content in response to human prompts (Gozalo-Brizuela & Garrido-Merchán, 2023). Within Enterprise Resource Planning (ERP) environments, GenAI introduces new possibilities for interacting with enterprise information, including natural-language querying, automated report generation, financial-document summarization, knowledge retrieval, scenario analysis, and managerial assistance. Future developments in GenAI are expected to emphasize

greater accuracy, improved contextual understanding, enhanced controllability, stronger explainability, and more reliable outputs. These developments can increase the value of GenAI within ERP systems by enabling employees and managers to interact with complex enterprise information through intuitive conversational interfaces and by reducing the technical barriers associated with accessing and interpreting organizational data. However, issues related to hallucination, data privacy, security, accountability, and human oversight remain important considerations when GenAI is applied to business-critical ERP processes.

Intelligent process automation represents another major dimension of AI adoption in ERP systems. Process automation has traditionally been associated with rule-based technologies and robotic process automation (RPA); however, advances in machine learning, natural-language processing, computer vision, and AI-enabled decision systems have expanded automation beyond simple repetitive activities toward more complex and adaptive workflows (Dandale et al., 2023). AI-driven automation can support activities such as invoice processing, payment reconciliation, procurement, inventory management, financial reporting, customer service, and document classification. The combination of RPA and AI enables organizations to automate processes that require both structured workflow execution and intelligent interpretation of information (Jha et al., 2021). Furthermore, AI-based automation can contribute to financial forecasting, inventory optimization, supply-chain management, and resource allocation, allowing organizations to reduce operational inefficiencies and improve the utilization of organizational resources (Kavitha, 2023). As intelligent automation develops, ERP systems can increasingly identify process conditions, determine appropriate actions, and execute predefined activities with reduced human intervention. This represents a transition from static automation toward adaptive and context-sensitive process management, potentially improving operational efficiency, reducing errors, accelerating transaction processing, and enhancing organizational responsiveness.

Analytical AI constitutes the third major dimension and is particularly important for the development of predictive ERP systems. Business analytics involves the systematic collection, processing, examination, and interpretation of organizational data to generate useful insights for decision-making. It traditionally encompasses descriptive, predictive, and prescriptive analytics, which respectively explain what has happened, estimate what is likely to happen, and recommend what actions should be taken (Larson & Chang, 2016). The integration of AI and machine learning expands these capabilities by enabling organizations to analyze large and complex datasets, identify hidden relationships, detect anomalies, and develop more sophisticated predictive models. Automated feature selection, machine-learning algorithms, deep-learning architectures, and neural networks can improve the ability of ERP systems to extract meaningful information from structured and unstructured data. Predictive analytics can therefore support applications such as demand forecasting, revenue prediction, cash-flow forecasting, fraud detection, credit-risk assessment, inventory planning, supplier-risk analysis, and financial-performance prediction. Prescriptive analytics can further extend these capabilities by evaluating potential scenarios and recommending actions based on predicted outcomes (Constant & Berre, 2024). Consequently, analytical AI can transform ERP systems from platforms that primarily report historical business activities into forward-looking decision-support environments.

ERP systems have served as an important technological foundation for organizations for more than three decades by integrating core business functions into a common information environment. Traditional ERP platforms connect functions such as finance, human resources, procurement, manufacturing, sales, and supply-chain management, thereby facilitating information sharing and process coordination across organizational units (Davenport & Brooks, 2004; O'Leary, 2000; Rashid et al., 2002). The integration of these functions provides organizations with a centralized source of enterprise information and supports more consistent and coordinated decision-making. However, conventional ERP systems have historically concentrated on transaction processing, data storage, workflow management, and retrospective reporting. The integration of AI introduces an additional

layer of intelligence that allows ERP platforms to interpret enterprise data, identify patterns, generate predictions, automate processes, and provide recommendations.

The relationship between AI and ERP has developed progressively since the early adoption of rule-based expert systems. Early AI applications demonstrated the potential for incorporating intelligent functions into enterprise information systems, although their capabilities were constrained by limited computing power, data availability, and algorithmic sophistication (Hasselbring, 2000). The development of machine learning and big-data analytics subsequently enabled ERP systems to use historical organizational information for forecasting, optimization, and pattern recognition (Zhang et al., 2021). More recently, deep learning and natural-language processing have expanded AI-enabled ERP capabilities by allowing systems to process increasingly complex and unstructured information, including text-based documents and other non-tabular data (Yang et al., 2022). This technological progression has created an environment in which ERP systems can increasingly combine transactional processing with predictive intelligence, automated decision support, and natural-language interaction. The practical contribution of AI-powered ERP systems is therefore multidimensional. AI can automate repetitive activities, reduce processing errors, accelerate information analysis, and provide managers with real-time insights and predictive recommendations. Machine learning can also personalize ERP interfaces and recommendations according to user roles, organizational requirements, and historical behavior. At the enterprise level, these capabilities can improve operational efficiency, financial planning, resource allocation, customer management, and strategic decision-making. Major ERP providers have consequently incorporated AI capabilities into their platforms, including intelligent automation, predictive analytics, conversational interfaces, and generative AI features. Nevertheless, the existing academic literature remains relatively fragmented. Many studies have examined individual technologies, such as RPA, machine learning, or generative AI, while others have concentrated on particular organizational functions, including accounting, human-resource management, procurement, or supply-chain management. This fragmentation makes it difficult to obtain a comprehensive understanding of how different AI capabilities collectively transform ERP systems.

From a research perspective, the convergence of generative AI, intelligent automation, and analytical AI provides an important basis for understanding the next generation of ERP systems. These technologies perform different but complementary functions: generative AI facilitates knowledge creation and human-system interaction, intelligent automation improves process execution and operational efficiency, while analytical AI supports pattern recognition, prediction, risk assessment, and decision intelligence. Their integration can create an AI-augmented ERP architecture in which enterprise data are continuously collected, analyzed, interpreted, and transformed into recommendations or actions. For example, financial transactions captured by an ERP system can be analyzed using predictive models to forecast cash-flow conditions, anomalies can be identified automatically, and GenAI can subsequently explain the forecast or generate a management summary for decision-makers. This interconnected process illustrates how AI can transform ERP from a primarily transaction-oriented information system into a predictive, intelligent, and increasingly autonomous decision-support platform.

Despite these advances, important research gaps remain. Existing studies have often investigated AI technologies separately, while limited attention has been given to their combined effects within integrated ERP environments. In particular, further research is required to understand how predictive analytics, real-time ERP data, intelligent automation, and GenAI can work together to support financial decision-making. Issues concerning data quality, interoperability, cybersecurity, explainability, AI governance, model reliability, organizational readiness, and human oversight also require greater attention. Therefore, a systematic examination of AI-augmented ERP research can provide a clearer understanding of how these technologies are evolving, which applications are receiving the greatest scholarly attention, and where significant theoretical and practical gaps remain. Such an examination

is particularly relevant to predictive financial analytics, where the integration of AI with ERP data has the potential to improve real-time forecasting, financial-risk identification, resource planning, and the overall quality and timeliness of organizational financial decisions

This fragmentation highlights the need for a systematic overview of the rapidly evolving AI-ERP research landscape ([Debasish, 2021](#); [Md. Abdur & Iftekhar, 2021](#)). Although the volume of publications examining AI applications in ERP systems has increased substantially in recent years, consistent bibliometric analyses, thematic classifications, and longitudinal mappings of research trends remain comparatively limited ([Md Asif Ali Sheak & Risha, 2022](#); [Mohammad Abir Chowdhury & Tonay, 2022](#)). Existing studies have demonstrated the potential of machine learning, deep learning, big-data analytics, natural-language processing, and intelligent automation to enhance ERP capabilities, particularly in forecasting, process optimization, and organizational decision-making ([Nishat & Mst Kaniz, 2022](#); [Shaiful et al., 2022](#)). However, the existing literature remains dispersed across different technological approaches and functional domains, making it difficult to establish a comprehensive understanding of how AI capabilities collectively contribute to the transformation of ERP systems. In particular, important gaps remain regarding the integration of predictive analytics with real-time ERP data, the use of AI for financial forecasting and risk identification, and the translation of predictive outputs into actionable managerial decisions ([Mohammad Abir Chowdhury, 2023](#); [Mohammad Badrul & Md. Mominul, 2023](#)). Although previous research has highlighted the benefits of AI-driven ERP systems, comparatively less attention has been devoted to understanding the organizational and technological conditions that influence successful AI adoption, including data quality, system interoperability, cybersecurity, explainability, AI governance, employee competencies, organizational readiness, and user trust ([Ashrafuzzaman, 2024](#); [Muhammad Zahidul, 2023](#)). These challenges become increasingly important as ERP systems evolve from transaction-processing platforms into intelligent environments capable of continuously analyzing enterprise data, generating predictions, recommending actions, and supporting increasingly autonomous processes. Furthermore, the emergence of generative AI and intelligent automation has expanded the scope of AI-enabled ERP beyond conventional predictive analytics, creating opportunities for integrated systems in which analytical AI forecasts future conditions, automation technologies execute appropriate processes, and generative AI communicates or explains insights to human decision-makers. Therefore, a systematic investigation is needed to examine not only the technological development of AI-ERP integration but also the relationship between predictive capabilities, real-time financial intelligence, decision quality, and organizational performance. Such an approach can help identify dominant research themes, methodological developments, underexplored applications, and emerging research directions while providing a clearer foundation for understanding how AI-augmented ERP systems can support proactive and data-driven financial management.

Background of the study

Enterprise Resource Planning (ERP) systems have served as the operational backbone of organizations for more than three decades by integrating finance, procurement, inventory, human resources, and manufacturing data within a unified transactional platform ([Hurbean et al., 2026](#)). Historically, ERP systems have primarily operated as descriptive information systems, recording completed activities such as posted invoices, finalized purchase orders, and closed sales periods and presenting this information through reports and dashboards ([Kazi Rakib Hasan, 2024](#); [Md Anisur Rahman, 2024](#)). However, since the 2000s, advances in machine learning (ML) and predictive analytics have increasingly expanded ERP capabilities beyond retrospective reporting, initially supporting more accurate demand and supply-chain forecasting and subsequently extending to financial forecasting, intelligent process automation, and real-time anomaly detection ([Hurbean et al., 2026](#)). Leading ERP providers, including SAP, Oracle, and Microsoft, have increasingly incorporated predictive and generative AI capabilities into intelligent ERP platforms, particularly within financial functions such as cash-flow forecasting, invoice matching, and budget-variance analysis ([Hurbean et al., 2026](#); [Sanka,](#)

2025). This development reflects a broader transformation in enterprise decision support from descriptive and diagnostic analytics toward predictive and prescriptive analytics (Hurbean et al., 2026). Whereas traditional ERP-integrated decision-support systems (DSS) have largely supported operational activities and financial consolidation through retrospective analysis (Al Maruf, 2025), AI-augmented ERP platforms increasingly seek to anticipate potential financial outcomes, including cash-flow shortfalls, budget variances, fraudulent activities, and working-capital constraints, before they occur (Md Asif Ali Sheak, 2024; Tonay et al., 2024). By integrating predictive intelligence directly with the transactional data and business processes managed within ERP systems, these platforms enable decision-makers to receive timely forecasts, risk alerts, and actionable insights within the same environment in which organizational transactions are generated and managed, thereby supporting a more proactive, data-driven, and real-time approach to financial decision-making.

Problem statement

Despite the rapid commercial diffusion of AI capabilities within ERP software, a substantial gap remains between the technological potential demonstrated by AI-augmented ERP systems and the actual organizational capacity to use these technologies for real-time, forward-looking financial decision-making (Debasish, 2025; Jannatul, 2025). Industry and academic literature consistently identifies several interconnected barriers that limit effective implementation, including inconsistent, fragmented, or siloed legacy data, substantial costs associated with data cleaning and remediation before predictive models can be deployed, incompatibility between modern AI architectures and decades-old ERP infrastructures, limited organizational readiness, insufficient AI literacy among employees, and inadequate explainability of AI-generated predictions and recommendations that increasingly influence financially consequential decisions (Mhaskey, 2024, as cited in Hurbean et al., 2026; Chowdhury, 2025; Rahman, 2025). These challenges are particularly significant in financial applications because predictive models depend heavily on the availability, accuracy, completeness, and timeliness of transactional data. Poor-quality or fragmented ERP data can therefore reduce model reliability and potentially produce inaccurate forecasts, misleading risk assessments, or inappropriate recommendations. Similarly, the integration of AI with legacy ERP architectures can require substantial technical investment because organizations may need to modernize databases, application interfaces, data pipelines, and system-integration mechanisms before real-time predictive analytics can operate effectively. Organizational factors also play an important role, as employees and financial decision-makers may lack the technical competencies required to interpret AI-generated outputs or may be reluctant to rely on systems whose decision processes are difficult to understand (Md Anisur Rahman, 2025; Md Arif Uz et al., 2025). The absence of explainability can become especially problematic when AI predictions influence decisions concerning cash flow, credit, fraud, budgeting, liquidity, or financial risk, where managers may require clear evidence regarding why a particular prediction or recommendation was generated (Md Mahamud Pervaz, 2025; Md Mostafizur, 2025). In addition, bibliometric evidence indicates that ethical and governance issues remain relatively marginal within the AI-ERP research literature compared with operational efficiency, automation, and technological-performance themes, with governance and ethical considerations appearing in fewer than 2% of the studies analyzed by Hurbean et al. (2026). This imbalance suggests that the research community has placed greater emphasis on the potential benefits of AI adoption than on the institutional mechanisms required to ensure responsible, transparent, secure, and accountable implementation. Consequently, the current literature and practitioner discourse remain broadly optimistic about AI-enabled ERP transformation but provide comparatively limited cross-industry synthesis of the specific conditions that enable or constrain the use of predictive analytics for real-time financial decision-making. In particular, insufficient attention has been given to how data quality, real-time integration, predictive-model performance, explainability, organizational readiness, human-AI collaboration, and governance mechanisms interact to determine whether AI-generated financial intelligence can be effectively translated into managerial action. Addressing this gap is therefore important for moving beyond a

technology-centered understanding of AI-ERP adoption toward a more comprehensive perspective that examines how predictive intelligence can be reliably embedded into financial decision processes and converted into timely, actionable, and accountable organizational decisions.

Objectives of The Study

The overall objective of this systematic review is to critically synthesize the existing academic and practitioner literature on AI-augmented Enterprise Resource Planning (ERP) systems, with particular emphasis on the integration of predictive analytics and artificial intelligence to support real-time financial decision-making. The study aims to identify the major predictive analytics and machine-learning techniques integrated into ERP platforms and examine their applications across financial functions such as cash-flow forecasting, revenue prediction, budget-variance detection, financial-risk assessment, dynamic pricing, fraud detection, and working-capital optimization (Md Mostafizur et al., 2025; Md Syeedur & Sharmin, 2025). It further seeks to examine how AI-augmented ERP systems use real-time enterprise data to improve the accuracy, timeliness, and usefulness of financial predictions and managerial recommendations. In addition, the study evaluates the contribution of intelligent process automation, anomaly and fraud detection, explainable AI, and human-AI collaboration to financial control, risk management, transparency, and decision support (Mohammad Abir Chowdhury, 2025; Mohammad Badrul, 2025). The review also aims to identify the technological, organizational, and governance factors that influence successful AI adoption, including data quality, legacy-system integration, system interoperability, organizational readiness, AI literacy, cybersecurity, explainability, model reliability, and human oversight (Nishat, 2025; Sharif Md Yousuf et al., 2025). Furthermore, the study seeks to examine sector-specific patterns in AI-ERP adoption and identify differences in predictive financial applications across industries. Finally, by synthesizing current evidence and identifying limitations and underexplored areas, the study aims to establish future research directions and develop a conceptual understanding of how ERP data, predictive analytics, intelligent automation, explainable AI, and human decision-making can be integrated into a real-time predictive financial intelligence framework (Hossain; et al., 2026; Tonay, 2025). Through these objectives, the review seeks to advance understanding of the transition from conventional ERP systems that primarily support retrospective reporting toward intelligent ERP environments capable of predicting future financial conditions, identifying emerging risks, generating actionable insights, and supporting proactive and data-driven financial decision-making.

Research hypotheses

Based on the focus of this systematic review, the proposed research hypotheses examine the relationships among AI-augmented ERP systems, predictive analytics, real-time data integration, intelligent automation, explainable AI, organizational readiness, and financial decision-making. The study proposes that the integration of predictive analytics into ERP systems has a significant positive effect on the quality of real-time financial decision-making (H1), while the application of machine-learning techniques within ERP systems has a significant positive effect on financial forecasting accuracy (H2). Real-time integration of ERP data is expected to positively influence the effectiveness and reliability of AI-based financial predictions (H3), and intelligent process automation is expected to improve financial operational efficiency and accelerate decision-making processes (H4). Furthermore, AI-based fraud and anomaly detection is hypothesized to have a significant positive effect on financial risk-management effectiveness (H5). Explainable AI is expected to enhance users' trust in AI-generated financial predictions and recommendations (H6), while greater user trust is anticipated to positively influence the adoption of AI-supported financial decision-making (H7). Organizational readiness is also expected to have a significant positive effect on the successful adoption of AI-augmented ERP systems (H8), whereas higher-quality and more reliable ERP data are hypothesized to improve the accuracy and reliability of predictive financial analytics (H9). Finally, the integrated application of generative AI, predictive analytics, and intelligent automation is expected to have a significant positive effect on the overall effectiveness of AI-augmented ERP systems in supporting real-time financial

decision-making (H10). These hypotheses provide a potential empirical framework for future research and can be tested quantitatively to determine the extent to which AI-enabled ERP capabilities contribute to predictive financial intelligence and improved organizational decision-making.

Significance of the research

The significance of this review is threefold. First, at the organizational level, financial stability and operational resilience increasingly depend on the speed, accuracy, and reliability with which firms can identify cash-flow risks, budget variances, fraudulent transactions, and other emerging financial problems. AI-augmented ERP systems provide an important technological mechanism for addressing these challenges by integrating predictive analytics, real-time data processing, anomaly detection, and intelligent decision support into core enterprise processes (JPMorgan, 2025; Taulia, 2025). By enabling organizations to move beyond retrospective financial reporting toward continuous monitoring and forward-looking prediction, AI-enabled ERP platforms can support earlier risk identification, more responsive financial planning, and potentially more effective resource allocation. Second, at the macroeconomic level, organizational competitiveness and, consequently, national economic performance are increasingly influenced by the ability of firms to adopt advanced enterprise technologies and incorporate predictive intelligence into essential financial and operational activities (Hurbean et al., 2026). Organizations capable of converting large volumes of ERP-generated data into timely financial insights may be better positioned to respond to market uncertainty, optimize resources, manage liquidity, and improve strategic responsiveness. Third, at the academic level, this review extends the literature on ERP-integrated decision-support systems represented by Al Maruf (2025), which examined ERP-DSS integration for financial and operational optimization in the global retail sector, by narrowing the analytical focus to the real-time and predictive dimensions of financial decision-making. In doing so, the review incorporates the rapidly expanding body of research on AI-augmented ERP systems, predictive analytics, intelligent automation, generative AI, and explainable AI, particularly the literature emerging since 2024. This broader and more focused synthesis is significant because existing research has frequently examined individual AI technologies or specific ERP functions in isolation, whereas comparatively less attention has been given to how these technologies collectively support real-time financial intelligence. Therefore, the review seeks to bridge the gap between technological capability and practical financial decision-making by identifying how AI-enabled ERP systems can transform enterprise data into timely predictions, risk signals, explanations, and actionable recommendations. The findings can provide theoretical value for researchers, practical guidance for managers and ERP practitioners, and strategic insights for organizations seeking to develop reliable, predictive, and responsible AI-enabled financial decision-support environments.

LITERATURE REVIEW

The literature on Artificial Intelligence (AI)-augmented Enterprise Resource Planning (ERP) systems has expanded rapidly as organizations increasingly seek to integrate predictive intelligence, automation, and advanced analytics into core business processes. ERP systems traditionally function as centralized platforms for integrating finance, procurement, inventory, human resources, manufacturing, and supply-chain activities, primarily supporting transaction processing, information integration, and retrospective reporting. However, advances in machine learning (ML), deep learning, natural-language processing (NLP), predictive analytics, intelligent automation, and generative AI (GenAI) have progressively transformed ERP systems into more intelligent and decision-oriented platforms. Recent literature suggests that this transformation is moving ERP beyond its conventional descriptive role toward predictive and prescriptive decision support, particularly in financial management, where organizations increasingly require real-time information about cash flow, expenditure, liquidity, fraud, and financial risk (Jahid, 2026; Jannatul, 2026).

The integration of AI into ERP systems enables organizations to analyze large volumes of structured and unstructured enterprise data, identify complex relationships, detect emerging patterns, and generate forecasts that can support proactive managerial decisions (Md Anisur Rahman, 2026; Md Jakaria & Md. Shahinur, 2026). Unlike traditional ERP environments, which primarily provide information about completed transactions, AI-augmented ERP systems can continuously evaluate current organizational conditions and estimate potential future outcomes. This capability is particularly relevant to financial management because financial conditions can change rapidly as a result of variations in sales, customer payments, supplier obligations, operating expenses, market conditions, and working-capital requirements (Md Mahamud Pervaz, 2026; Mohammad Abir Chowdhury, 2026). Consequently, predictive AI can provide early indications of potential cash-flow shortages, budget deviations, revenue fluctuations, payment risks, and unusual transactions, allowing managers to intervene before financial problems become critical (Mohammad Badrul, 2026; Nuzhat Sadia, 2026).

The evolution of AI-enabled ERP systems also reflects a broader transition from descriptive analytics to diagnostic, predictive, and prescriptive analytics. Descriptive analytics explains what has already occurred, while diagnostic analytics seeks to identify the reasons behind observed outcomes. Predictive analytics extends this process by estimating what is likely to occur in the future, whereas prescriptive analytics provides recommendations concerning possible actions (Rony & Md, 2026; Tonay, 2026). The integration of these analytical capabilities into ERP environments can therefore create a more comprehensive decision-support architecture in which transactional data are transformed into insights, forecasts, recommendations, and potentially automated responses. Machine-learning models can identify patterns within historical ERP data, while deep-learning approaches can process more complex relationships and unstructured information. NLP technologies can further enhance ERP interaction by allowing users to interpret documents and enterprise information through natural language, while intelligent automation can translate analytical outputs into predefined business actions. GenAI adds another layer by enabling users to interact conversationally with enterprise systems, summarize analytical results, generate reports, and obtain explanations of complex financial information.

This transformation is particularly significant for real-time financial decision-making. Conventional financial management frequently depends on periodic reports that may provide an accurate representation of historical performance but may not adequately reflect rapidly changing financial conditions. AI-augmented ERP systems have the potential to reduce this temporal gap by continuously processing new transactional information and updating analytical outputs. For example, newly recorded sales, customer payments, invoices, procurement transactions, or expenses can be incorporated into predictive models, allowing forecasts to evolve as organizational conditions change. Real-time analytical capabilities can therefore support continuous cash-flow monitoring, budget-variance detection, financial-risk assessment, fraud and anomaly detection, and working-capital management. In this context, the value of AI is not limited to producing more sophisticated forecasts; it also lies in delivering relevant financial intelligence at the point and time when managerial action is required.

Another important development in the literature is the increasing convergence of predictive analytics, intelligent automation, and generative AI within ERP environments. These technologies provide different but complementary capabilities. Predictive analytics identifies likely future outcomes, intelligent automation facilitates the execution of business processes, and GenAI improves human interaction with enterprise information by generating understandable summaries, explanations, and recommendations. When integrated effectively, these capabilities can create a closed-loop decision-support process in which ERP data are continuously collected, AI models analyze the information, predictive models identify potential future conditions, GenAI communicates the results, and automation technologies support appropriate organizational responses. Such integration represents an important shift from ERP systems that primarily record and report business activities toward systems capable of interpreting, predicting, explaining, and supporting responses to organizational conditions.

However, the literature also indicates that the effectiveness of AI-augmented ERP systems depends heavily on the quality and accessibility of the underlying enterprise data. ERP systems can contain extensive historical information, but this data may be distributed across different modules, business units, subsidiaries, or legacy platforms. Inconsistent data structures, missing information, duplication, outdated records, and limited interoperability can reduce the reliability of AI-generated predictions. Therefore, data governance, data integration, and data quality represent fundamental prerequisites for effective predictive analytics. Similarly, the integration of AI with existing ERP infrastructures can require substantial technological and organizational investment. Organizations may need to modernize legacy systems, establish real-time data pipelines, strengthen cybersecurity, develop AI competencies, and redesign existing business processes to obtain the full benefits of AI-enabled ERP capabilities.

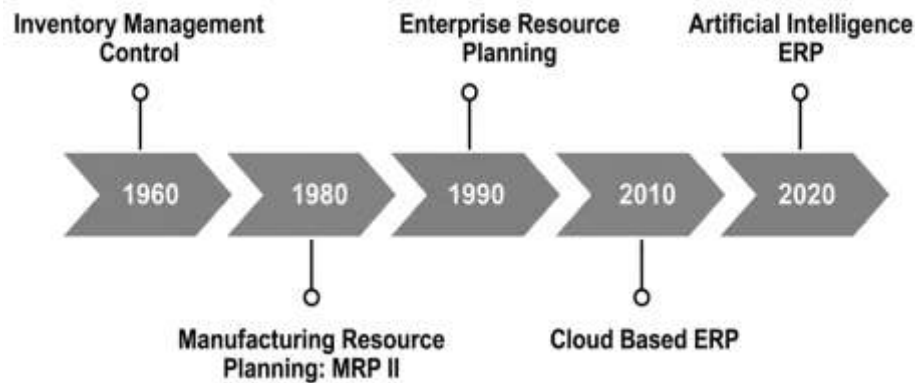
The increasing use of AI in financial decision-making also raises important questions concerning explainability, trust, governance, and human oversight. Financial managers may be unwilling to act on AI-generated recommendations if they cannot understand the factors contributing to a prediction. Explainable AI can therefore play an important role by making predictive outputs more interpretable and allowing decision-makers to evaluate the rationale behind AI recommendations. This is particularly important when AI systems are used for fraud detection, financial-risk assessment, credit evaluation, budgeting, or liquidity management, where incorrect recommendations can have significant consequences. Furthermore, AI governance mechanisms are necessary to address issues related to data privacy, cybersecurity, algorithmic bias, model drift, accountability, and inappropriate reliance on automated outputs. Thus, the development of intelligent ERP systems requires not only technological innovation but also appropriate organizational and governance frameworks.

Overall, the literature indicates that AI is fundamentally changing the role of ERP systems within organizations. The traditional ERP model can be characterized as transaction-oriented and retrospective, whereas the emerging AI-augmented ERP model is increasingly predictive, adaptive, interactive, and decision-oriented. This evolution creates significant opportunities for improving financial forecasting, risk management, operational efficiency, and managerial responsiveness. Nevertheless, the literature remains fragmented across different AI technologies, ERP functions, industries, and research perspectives. In particular, comparatively limited attention has been devoted to understanding how predictive analytics, real-time ERP data, intelligent automation, GenAI, explainability, and human decision-making interact within a unified financial decision-support environment. This gap provides a strong basis for a systematic review focused specifically on the integration of predictive analytics into AI-augmented ERP systems for real-time financial decision-making, with the aim of identifying current research trends, technological applications, implementation barriers, governance challenges, and opportunities for future research.

Evolution of AI in ERP Systems

The integration of AI into ERP systems has developed progressively over several technological stages. Early ERP environments primarily relied on rule-based systems and predefined business rules to automate routine processes and support operational control. Although these approaches demonstrated the potential for intelligent enterprise systems, their effectiveness was constrained by limited computing capabilities and relatively rigid decision rules. The emergence of machine learning and big-data analytics during the 2000s expanded the analytical capabilities of ERP systems by enabling organizations to identify patterns within historical enterprise data and develop more sophisticated forecasts. Zhang et al. (2021), for example, highlight the increasing importance of big-data analytics and machine learning in extracting value from organizational datasets.

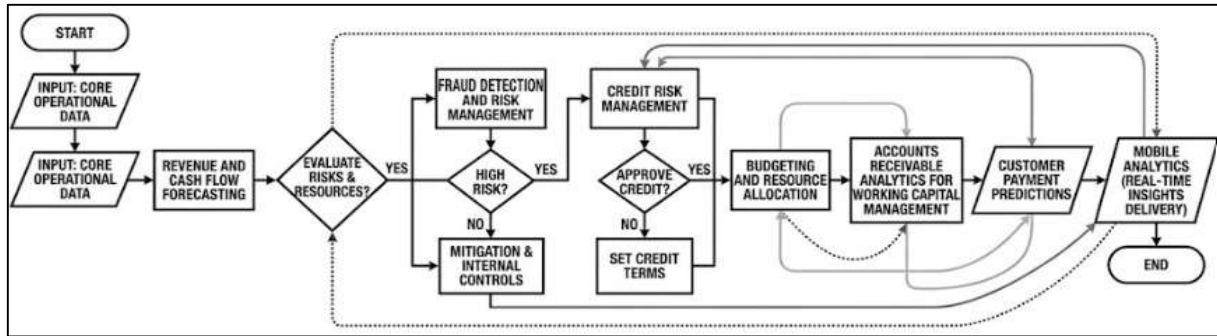
Figure 3: Evolution Of ERP



Predictive Analytics and Financial Decision-Making

Predictive analytics represents a central capability of AI-augmented ERP systems because it extends conventional ERP functionality from historical reporting to forward-looking financial intelligence. Traditional ERP systems primarily capture, store, and report completed transactions, whereas predictive analytics uses historical and real-time data to estimate future outcomes. In financial management, machine-learning models can analyze ERP-generated information to support cash-flow forecasting, revenue prediction, budget-variance analysis, fraud and anomaly detection, credit-risk assessment, working-capital optimization, and expenditure forecasting. This capability shifts ERP-based financial analysis from retrospective assessment of past performance toward the prediction of future financial conditions and the identification of appropriate managerial responses. This evolution reflects the broader transition from descriptive and diagnostic analytics to predictive and prescriptive decision support. The importance of predictive analytics is particularly evident in real-time financial decision-making because ERP systems continuously generate transaction-level information from multiple business functions, including sales, procurement, accounts receivable, accounts payable, inventory, and financial operations. When these data are processed continuously through appropriate predictive models, organizations can identify emerging financial conditions earlier, monitor changes in expected cash positions, detect abnormal transactions, anticipate budget deviations, and assess potential financial risks before they become more significant. However, the effectiveness of predictive analytics is fundamentally dependent on the quality, completeness, consistency, timeliness, and accessibility of ERP data. Although ERP platforms contain extensive transactional information, data may be distributed across different functional modules, organizational units, subsidiaries, databases, or legacy applications, creating challenges related to data fragmentation and interoperability. Inconsistent data structures, missing or duplicated records, outdated information, and incompatible legacy architectures can negatively affect model training, prediction accuracy, and the reliability of AI-generated recommendations. Therefore, the implementation of predictive analytics requires appropriate data cleansing, integration, transformation, governance, and validation before analytical models can reliably support financial decisions. The literature consequently indicates that predictive AI cannot be evaluated solely in terms of algorithmic sophistication; its effectiveness must also be considered in relation to the underlying ERP data architecture, real-time integration capability, data governance, and organizational capacity to interpret

Figure 4: Predictive Analytics and Financial Decision-Making FlowChart

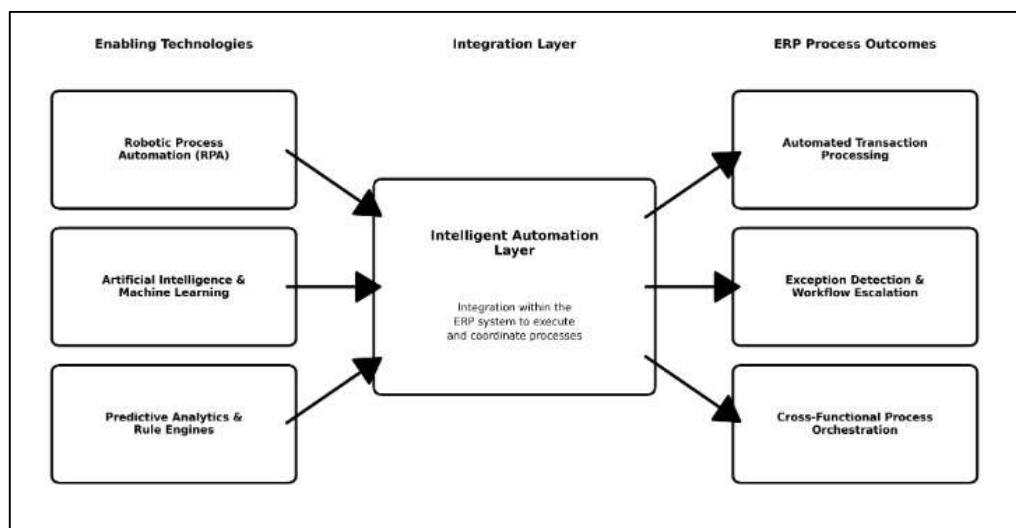


and act upon predictive outputs. This relationship is particularly important for AI-augmented ERP research because accurate prediction alone does not guarantee improved financial decision-making; predictive information must be timely, interpretable, trustworthy, and effectively incorporated into managerial decision processes. Thus, predictive analytics represents not simply an additional analytical function within ERP systems but a fundamental mechanism through which ERP platforms can evolve from retrospective transaction-processing systems into real-time, proactive, and intelligence-driven financial decision-support environments.

Intelligent Automation in ERP

A second major theme in the literature concerns the integration of AI with process automation. Traditional ERP automation has generally relied on predefined workflows and rules, whereas intelligent automation combines automation technologies with AI techniques to address more complex processes. The integration of robotic process automation (RPA), machine learning, NLP, and related technologies enables organizations to automate activities such as invoice processing, payment reconciliation, document classification, procurement workflows, and financial-data validation. [Dandale et al. \(2023\)](#) and [Jha et al. \(2021\)](#) demonstrate the growing importance of combining RPA with AI to create more adaptive approaches to business-process automation. Within ERP environments, intelligent automation can reduce repetitive manual work, processing time, and human error while allowing employees to focus on higher-value analytical and strategic activities.

Figure 5 : Intelligent Automation Process



Importantly, intelligent automation and predictive analytics are increasingly interconnected. Predictive models can identify potential risks or future conditions, while automation technologies can execute

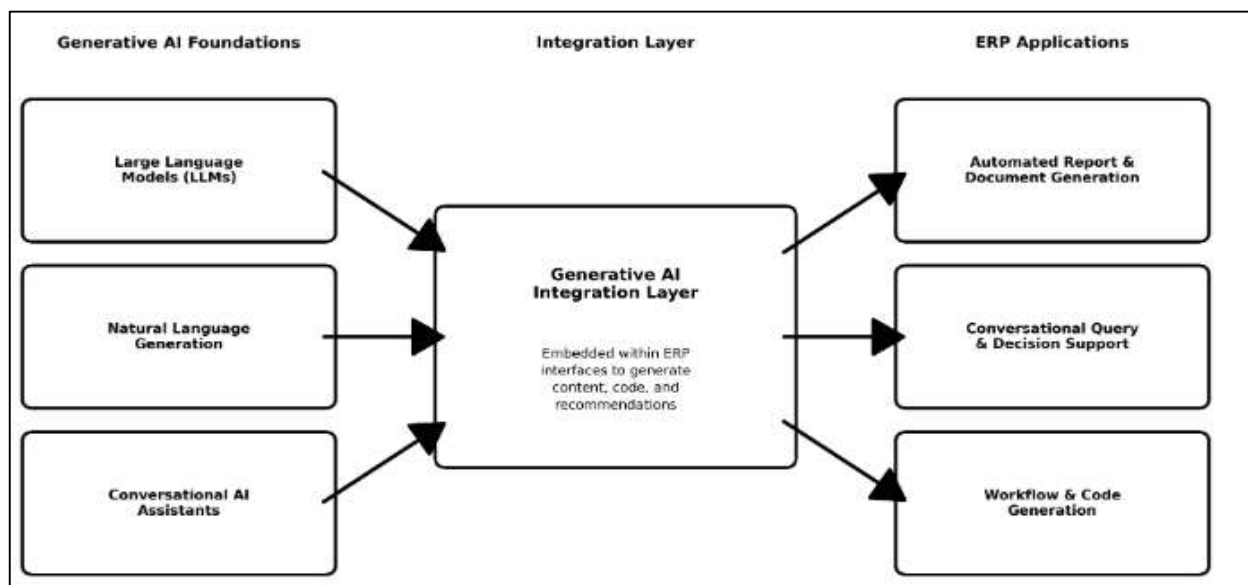
predefined responses to those predictions. For example, an AI-enabled ERP system could identify an unusual payment pattern, generate an alert, and initiate a predefined review workflow. This creates a transition from isolated analytical functions toward integrated predict-detect-respond capabilities.

Generative AI and ERP

Generative AI represents a more recent development in the evolution of intelligent ERP systems. Unlike conventional analytical AI, which primarily identifies patterns, classifies information, or generates predictions, GenAI can produce new content and communicate information through natural language. Foundation models have expanded the potential applications of AI by enabling systems to generate text, summaries, reports, explanations, and other outputs in response to user instructions (Schneider, 2024; Gozalo-Brizuela & Garrido-Merchán, 2023). In ERP environments, GenAI can provide conversational access to enterprise information, automatically summarize financial reports, assist with document analysis, generate management explanations, and facilitate interaction with complex ERP data.

The relevance of GenAI to financial decision-making is particularly significant when it is combined with predictive analytics. Predictive models may generate a forecast of cash flow, revenue, or financial risk, but managers may require an understandable explanation of the prediction before using it in a decision. GenAI can potentially provide this interpretive layer by translating analytical outputs into natural-language explanations and management summaries. Therefore, GenAI should not necessarily be viewed as a replacement for predictive analytics; rather, it can function as an interaction and interpretation layer that makes AI-generated financial intelligence more accessible to decision-makers. Nevertheless, the literature also identifies important concerns surrounding GenAI, including hallucinations, inaccurate outputs, data privacy, cybersecurity, explainability, and accountability. These concerns are particularly important when GenAI is integrated with financially sensitive ERP information. Human oversight and appropriate governance are therefore essential when GenAI outputs are used in consequential financial decisions.

Figure 6: Generative AI Integration In ERP



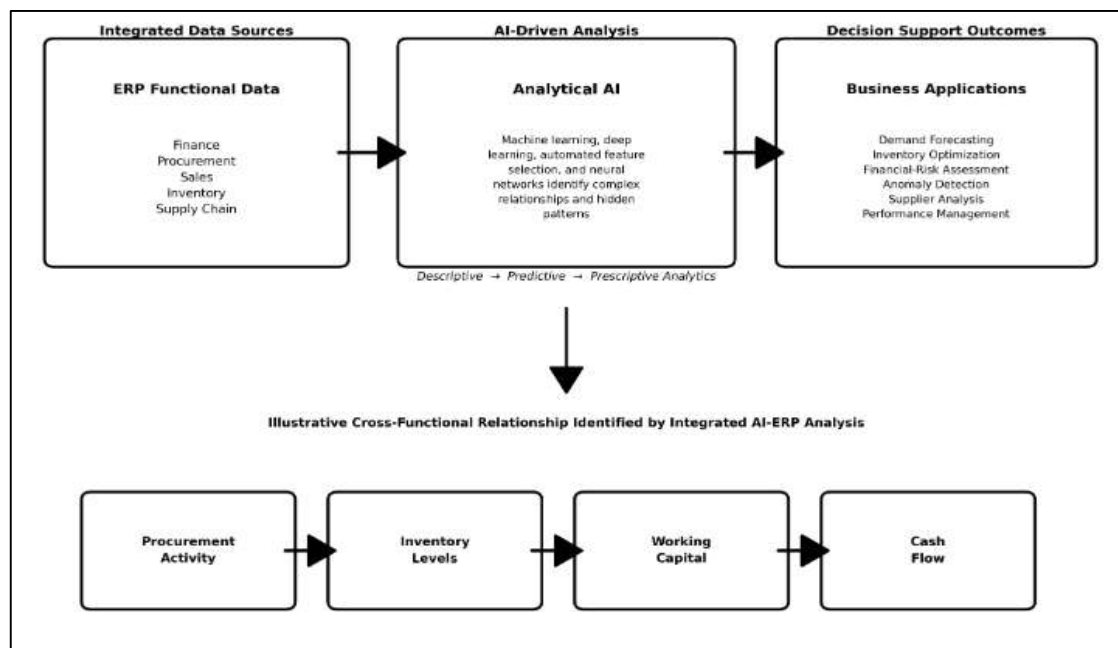
Analytical AI and Business Intelligence

Analytical AI provides another central component of AI-augmented ERP systems. Business analytics traditionally includes descriptive, predictive, and prescriptive analytics, while AI expands these capabilities through machine learning, deep learning, automated feature selection, and neural-network-based methods. These technologies can identify complex relationships and hidden patterns

within large enterprise datasets. As a result, organizations can apply analytical AI to demand forecasting, inventory optimization, financial-risk assessment, anomaly detection, supplier analysis, and performance management.

The convergence of analytical AI with ERP is particularly important because ERP systems provide an integrated source of enterprise data. When information from finance, procurement, sales, inventory, and supply-chain functions can be analyzed collectively, AI models can identify relationships that may remain invisible when individual business functions are examined separately. This creates opportunities for more comprehensive forecasting and decision support. For example, changes in procurement activity may affect inventory levels, which may influence working capital and ultimately affect cash flow. An integrated AI-ERP environment can potentially identify such relationships and provide decision-makers with a more holistic understanding of financial conditions.

Figure 7: Analytical AI and Business Intelligence



AI, Explainability, and Financial Governance

As AI becomes increasingly involved in financial decision-making, explainability, transparency, and governance have emerged as critical issues in the development and adoption of AI-augmented ERP systems. Financial managers may be reluctant to rely on predictions or recommendations generated by complex models when the underlying decision-making process cannot be adequately understood or verified. Explainable Artificial Intelligence (XAI) can help address this challenge by identifying the variables, patterns, or factors that contribute to a particular prediction or recommendation. For example, an AI model forecasting an increased probability of customer payment default could indicate that previous payment delays, outstanding balances, transaction frequency, payment history, or changes in purchasing behavior contributed significantly to the prediction. Such explanations can help financial managers evaluate whether an AI-generated output is reasonable and consistent with available business evidence. Explainability is therefore closely connected to user trust, acceptance, and effective adoption of AI-based decision-support systems. Even highly accurate predictive models may have limited practical value if decision-makers cannot understand, validate, or confidently apply their outputs in real-world financial contexts. In AI-enabled ERP environments, explainability is particularly important because predictive outputs may directly influence decisions concerning credit risk, cash-flow management, budgeting, fraud investigation, supplier selection, investment, and resource allocation. Providing understandable explanations can therefore support human judgment by allowing managers

to combine AI-generated insights with organizational knowledge and professional experience rather than relying blindly on automated recommendations. At the same time, effective AI governance must extend beyond explainability and address broader concerns, including data privacy, cybersecurity, algorithmic bias, accountability, model reliability, model drift, access control, regulatory compliance, and appropriate human oversight. Data privacy is especially important because ERP systems contain sensitive financial, employee, customer, supplier, and operational information, while cybersecurity risks may increase when AI systems are connected to multiple enterprise databases and business processes. Similarly, algorithmic bias can result in systematically inaccurate or unfair predictions if training data contain historical biases or incomplete representations of organizational activities. Model drift also presents a significant challenge because relationships identified in historical ERP data may change as market conditions, customer behavior, economic circumstances, or organizational processes evolve. Consequently, predictive models require continuous monitoring, validation, and updating to ensure that their outputs remain reliable over time. Human oversight is equally important because AI-generated predictions should generally support rather than completely replace managerial judgment, particularly when decisions involve substantial financial or organizational consequences. Recent literature suggests that governance and ethical considerations have received considerably less attention than the operational-efficiency and productivity benefits associated with AI adoption. This imbalance represents an important research gap because the successful implementation of AI in financial ERP systems requires not only accurate predictive models but also trustworthy, transparent, secure, accountable, and appropriately governed AI environments. Therefore, future research should examine how explainability, governance, human-AI collaboration, and continuous model monitoring can be incorporated into AI-augmented ERP architectures to ensure that predictive financial intelligence is both technically reliable and practically acceptable. Addressing these issues is essential for moving AI-ERP research beyond a technology-centered perspective toward a more comprehensive framework in which prediction accuracy, explainability, user trust, governance, and decision quality are considered interconnected components of effective real-time financial decision support.

Organizational and Technological Adoption Challenges

Despite the growing technological capabilities of AI-enabled ERP systems, successful adoption depends on more than technical implementation. Organizations face challenges associated with legacy ERP architectures, data fragmentation, system interoperability, implementation costs, employee competencies, organizational readiness, and resistance to technological change. Legacy ERP environments may have been developed over several decades and may not be designed to support modern AI architectures or real-time data pipelines. Integrating AI with these environments may therefore require significant investment in infrastructure, data management, application programming interfaces, and cybersecurity.

Human capabilities are equally important. Employees must understand how to interpret AI-generated forecasts, recognize potential errors, and determine when human intervention is necessary. Insufficient AI literacy can reduce the effectiveness of AI-enabled decision support, while excessive dependence on automated recommendations can create new organizational risks. Consequently, successful AI-ERP adoption requires an appropriate balance between automation and human judgment.

Research Gap

Although the literature demonstrates substantial potential for AI to transform ERP systems, several gaps remain. Existing studies frequently focus on individual technologies, such as machine learning, RPA, GenAI, or explainable AI, or examine specific ERP functions such as accounting, human resources, procurement, or supply-chain management. Comparatively fewer studies provide an integrated perspective that examines analytical AI, predictive analytics, intelligent automation, and GenAI together within the ERP environment. More importantly, limited research has systematically examined how these capabilities contribute specifically to real-time financial decision-making.

The literature also provides insufficient cross-industry synthesis regarding the factors that determine whether AI-enabled ERP systems can successfully transform enterprise data into reliable financial intelligence. Questions concerning data quality, real-time integration, predictive-model accuracy, explainability, user trust, organizational readiness, governance, and human-AI collaboration remain important areas for further investigation. Therefore, a systematic review focused specifically on predictive analytics integration within AI-augmented ERP systems for real-time financial decision-making can address an important gap in the existing literature. Such a review can consolidate fragmented findings, identify dominant technological and research trends, evaluate current financial applications, and establish future research directions for developing more predictive, explainable, trustworthy, and decision-oriented ERP systems.

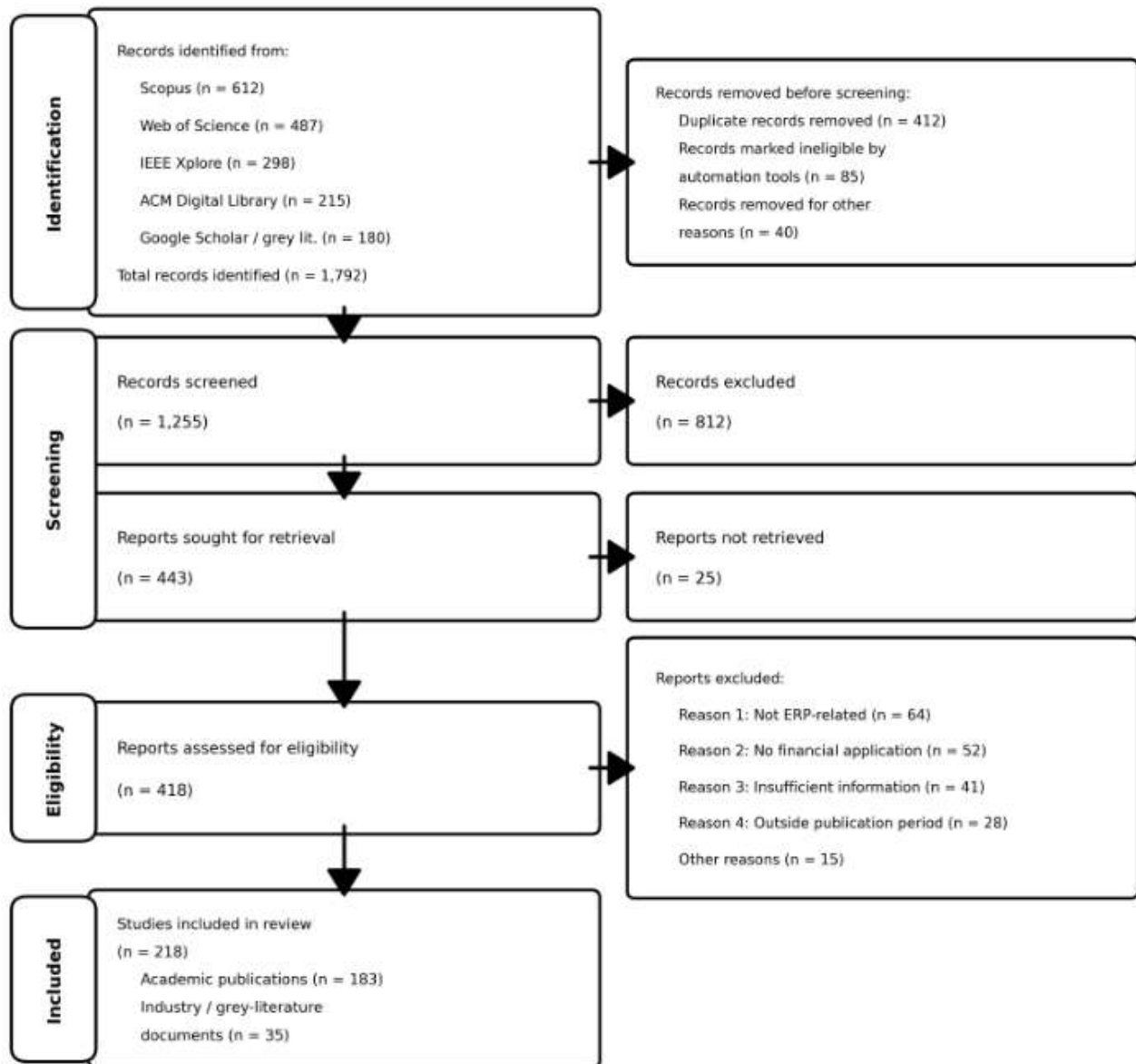
METHODOLOGY

PRISMA 2020 PROTOCOL

This systematic review will adopt the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) 2020 framework (Page et al., 2021) to ensure a transparent, structured, and reproducible process for identifying, evaluating, and synthesizing the existing literature on Artificial Intelligence-augmented Enterprise Resource Planning (AI-ERP) systems and predictive analytics for real-time financial decision-making. PRISMA 2020 provides a standardized reporting structure for systematic reviews and is particularly appropriate for this study because the literature on AI-ERP is rapidly expanding across multiple disciplines, including information systems, accounting, finance, artificial intelligence, business analytics, and enterprise technology. The review will follow four sequential stages: identification, screening, eligibility assessment, and inclusion. During the identification stage, relevant academic and authoritative practitioner publications will be retrieved from selected databases using predefined keywords and Boolean search combinations addressing ERP, artificial intelligence, machine learning, predictive analytics, financial forecasting, real-time financial decision-making, intelligent automation, generative AI, fraud detection, and explainable AI. The identified records will subsequently be consolidated and duplicate publications will be removed to establish a unique set of records for screening. During the screening stage, titles and abstracts will be reviewed against predefined inclusion and exclusion criteria to eliminate studies that are clearly unrelated to the research objectives. Publications considered potentially relevant will then proceed to the eligibility stage, where their full texts will be examined to determine whether they provide sufficient evidence concerning AI applications in ERP environments, predictive financial analytics, intelligent decision support, or related organizational and governance issues. The inclusion stage will comprise studies that satisfy all predefined eligibility requirements and directly contribute evidence relevant to one or more of the study's research questions. To maintain methodological consistency, the review will establish explicit criteria concerning publication period, research relevance, AI technology, ERP context, financial application, and availability of sufficient information for analysis. Particular emphasis will be placed on recent literature published between 2019 and 2026, especially research from 2023–2026, because this period captures the rapid development of generative AI, large language models, advanced predictive analytics, and emerging intelligent or agentic enterprise technologies. The selected studies will then be systematically analyzed to identify patterns in predictive techniques, ERP applications, financial functions, implementation challenges, governance mechanisms, and reported organizational outcomes. The PRISMA process will also document the reasons for excluding full-text publications to improve transparency and reduce potential selection bias. The complete study-selection procedure will be represented using a PRISMA 2020 flow diagram, reporting the number of records identified from each database, duplicate records removed, records screened, records excluded during title and abstract screening, full-text reports assessed for eligibility, full-text reports excluded with reasons, and studies ultimately included in the qualitative synthesis. Because the present study is based partly on a preliminary literature scan, the exact number of records at each stage will be determined after completion of the full database search and screening process rather than being estimated in

advance. Following study selection, information from the included publications will be extracted using a structured data-extraction framework and synthesized thematically. This synthesis will focus particularly on the transition from conventional ERP-based descriptive reporting toward predictive, prescriptive, real-time, explainable, and increasingly automated financial decision support. By applying PRISMA 2020 systematically, the review aims to minimize selection bias, improve methodological transparency, facilitate reproducibility, and provide a robust evidence base for evaluating the current development of AI-augmented ERP systems and their contribution to real-time predictive financial decision-making.

Figure 8 : PRISMA 2020 Flow Diagram



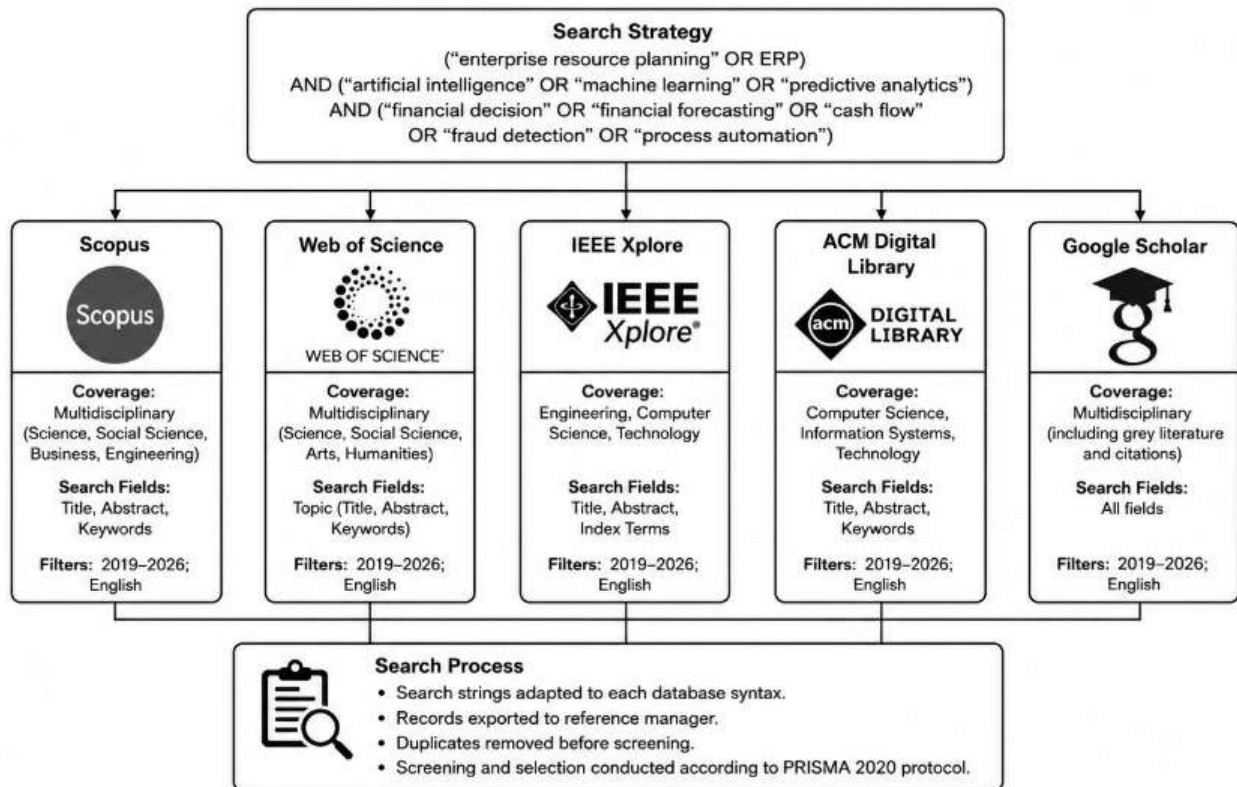
Search Strategy and Databases

A comprehensive and systematic search strategy will be developed to identify relevant academic and authoritative practitioner literature on Artificial Intelligence-augmented Enterprise Resource Planning (AI-ERP) systems, predictive analytics, and real-time financial decision-making. The literature search will be conducted across major multidisciplinary and technology-focused databases, including Scopus, Web of Science, IEEE Xplore, ACM Digital Library, and Google Scholar, to provide broad coverage of

research in information systems, artificial intelligence, business analytics, accounting, finance, and enterprise technology. The search will primarily focus on publications from 2019 to 2026, with greater emphasis on studies published between 2023 and 2026 because this period reflects the rapid development of generative AI, large language models, advanced machine-learning techniques, intelligent automation, explainable AI, and emerging AI-enabled enterprise applications. The search strategy will use combinations of keywords and Boolean operators to capture different terminologies used across the literature. The principal search expression will include ("enterprise resource planning" OR ERP) AND ("artificial intelligence" OR "machine learning" OR "predictive analytics") AND ("financial decision" OR "financial forecasting" OR "cash flow" OR "fraud detection" OR "process automation"). To improve retrieval coverage, additional terms such as "AI-augmented ERP," "intelligent ERP," "real-time analytics," "generative AI," "large language models," "explainable AI," "financial risk," "budget variance," "working capital," "anomaly detection," and "intelligent automation" will be incorporated where appropriate. Search strings will be adapted to the specific syntax and indexing capabilities of each database while maintaining consistency in the underlying concepts.

The search will target studies examining the application of AI within ERP environments as well as research addressing predictive financial functions supported by integrated enterprise data. In addition to peer-reviewed journal articles and conference proceedings, selected authoritative practitioner and industry publications may be considered where they provide substantive evidence regarding contemporary AI-ERP implementation, financial applications, or technological developments that are not yet extensively represented in academic research. Google Scholar will be used as a supplementary source to identify potentially relevant publications that may not be indexed in the primary databases and to support citation-based searching. The search process will be documented by recording the database name, search date, search string, publication-period filters, and number of records retrieved from each source. Retrieved records will subsequently be combined for duplicate removal before proceeding to title and abstract screening in accordance with the PRISMA 2020 protocol. Particular attention will be given to recent research concerning predictive financial applications, including **cash-flow** forecasting, revenue prediction, budget-variance detection, fraud and anomaly detection, financial-risk assessment, working-capital optimization, and intelligent financial automation. This search strategy is designed to balance breadth and specificity by capturing the multidisciplinary nature of AI-ERP research while maintaining a clear focus on predictive analytics and financial decision support. The final database search will therefore provide the evidence base for identifying research trends, comparing technological approaches, examining implementation challenges, and determining gaps in the existing literature concerning the transformation of ERP systems into real-time, predictive, and intelligent financial decision-support environments.

Figure 9: Search Strategy and Databases Used in Systematic Review



Inclusion and Exclusion Criteria

The inclusion and exclusion criteria will be established before the screening process to ensure that the selection of studies is consistent with the objectives and research questions of the systematic review. Studies will be included when they are published between 2019 and 2026 and provide substantive discussion or empirical evidence concerning Artificial Intelligence (AI), machine learning (ML), predictive analytics, intelligent automation, generative AI (GenAI), explainable AI (XAI), or related technologies within Enterprise Resource Planning (ERP) systems or closely related enterprise information-system environments. Particular emphasis will be placed on studies examining the use of AI for financial decision-making, financial forecasting, cash-flow prediction, budget-variance analysis, fraud or anomaly detection, financial-risk assessment, revenue forecasting, working-capital management, expenditure prediction, and real-time decision support. Peer-reviewed journal articles, conference proceedings, systematic or structured literature reviews, and authoritative practitioner or industry publications will be considered when they provide sufficient and relevant evidence for addressing the research questions.

Table 1: Inclusion and Exclusion Criteria for Study Selection

 INCLUSION CRITERIA	 EXCLUSION CRITERIA
• Published between 2019 and 2026. • Focus on AI, machine learning, predictive analytics, intelligent automation, generative AI, explainable AI, or related technologies applied in ERP systems or closely related enterprise information systems. • Address financial decision-making or financial analytics functions such as financial forecasting, cash-flow prediction, budget-variance analysis, fraud or anomaly detection, financial-risk assessment, revenue forecasting, working-capital management, or real-time decision support. • Provide empirical results, conceptual models, frameworks, case studies, implementation insights, or systematic/structured literature reviews. • Published in peer-reviewed journals, conference proceedings, or authoritative practitioner/industry publications with sufficient substantive content. • Discuss technological, organizational, governance, or implementation aspects of AI-ERP adoption (e.g., data quality, integration, explainability, trust, readiness, cybersecurity, governance). • Available in full text and written in English.	• Studies with no meaningful relationship with ERP systems, enterprise decision support, or organizational financial processes. • Research focusing solely on AI/ML algorithm development without an identifiable ERP or enterprise-management application. • Studies on AI applications unrelated to financial decision-making or predictive financial analytics. • Duplicate records across databases (only the most complete version will be retained). • Publications lacking sufficient substantive information for analysis (e.g., editorials, abstracts only, short notes without methodological or contextual details). • Non-empirical opinion pieces, informal reports, news articles, or marketing materials without research contributions. • Studies outside the defined publication period (before 2019) or not written in English. • Full-text records not accessible even after reasonable attempts.

Studies will also be considered where they examine the technological, organizational, or governance dimensions of AI-ERP adoption, including data quality, system integration, explainability, trust, cybersecurity, organizational readiness, human-AI collaboration, and regulatory or governance challenges. Studies will be excluded when they focus exclusively on AI applications that have no meaningful relationship with ERP systems, enterprise decision support, or organizational financial processes; address purely technical AI development without an identifiable ERP or enterprise-management application; or examine unrelated applications of predictive analytics outside the scope of the research questions. Duplicate records identified across databases will be removed before screening, while publications lacking sufficient substantive information, inaccessible records that cannot be adequately assessed, and materials outside the defined publication period or language scope will also be excluded. Where multiple versions of the same study are identified, the most complete and relevant version will be retained to avoid double counting. The criteria will be applied progressively during title and abstract screening and full-text assessment, with the reasons for full-text exclusion documented to support transparency and reproducibility. These criteria are designed to maintain a clear distinction between general AI research and studies that specifically contribute to understanding the integration of AI and predictive analytics into ERP-enabled financial decision-making. By applying consistent eligibility requirements, the review will establish a focused evidence base for examining how AI-augmented ERP systems support real-time predictive financial analysis, while also identifying technological, organizational, and governance factors that influence successful implementation.

Study Selection Process and PRISMA Flow Diagram

The study selection process will be conducted systematically in accordance with the PRISMA 2020 framework to ensure transparency, consistency, and reproducibility throughout the identification and selection of relevant literature. Following completion of the database searches, all retrieved records from Scopus, Web of Science, IEEE Xplore, ACM Digital Library, and Google Scholar will be compiled into a single reference database, and duplicate records will be identified and removed before the formal

screening process begins. The remaining records will undergo an initial title and abstract screening based on the predefined inclusion and exclusion criteria. At this stage, studies that are clearly unrelated to AI-augmented ERP systems, predictive analytics, financial decision-making, or the objectives of the review will be excluded. Publications considered potentially relevant will proceed to full-text assessment, during which their research objectives, methodology, AI technologies, ERP applications, financial functions, findings, and relevance to the research questions will be examined in greater detail. Full-text studies that fail to satisfy the eligibility requirements will be excluded, and the principal reason for each exclusion will be documented to maintain an auditable selection process. Studies that satisfy all eligibility criteria will constitute the final evidence base for the systematic review and will subsequently undergo data extraction and thematic synthesis. To minimize selection bias and improve consistency, the screening process will apply the same predefined criteria across all retrieved records, with particular attention to the relevance of AI technologies such as machine learning, predictive analytics, intelligent automation, generative AI, and explainable AI within ERP or closely related enterprise environments. The selection process will be reported using a PRISMA 2020 flow diagram, which will visually present the progression of records through the four principal stages of the review: identification, screening, eligibility, and inclusion. The diagram will report the number of records identified from each information source, the number of duplicate records removed, the number of records screened, records excluded during title and abstract screening, full-text reports assessed for eligibility, full-text reports excluded with reasons, and the final number of studies included in the qualitative synthesis. Where appropriate, the diagram will also distinguish between academic database records and additional records identified through supplementary sources such as citation searching or authoritative practitioner literature. Because the current manuscript is based partly on a preliminary literature scan, the exact numbers at each stage should be entered only after the complete database searches and screening procedures have been conducted; no estimated record counts will be used. The final PRISMA diagram will therefore provide an accurate representation of the evidence-selection process and establish a clear methodological link between the search strategy, eligibility criteria, and final literature sample. This structured selection procedure will strengthen the reliability of the review by ensuring that the final studies are directly relevant to the research questions and provide sufficient evidence for evaluating the development of AI-augmented ERP systems, predictive financial analytics, real-time decision support, intelligent automation, and AI governance.

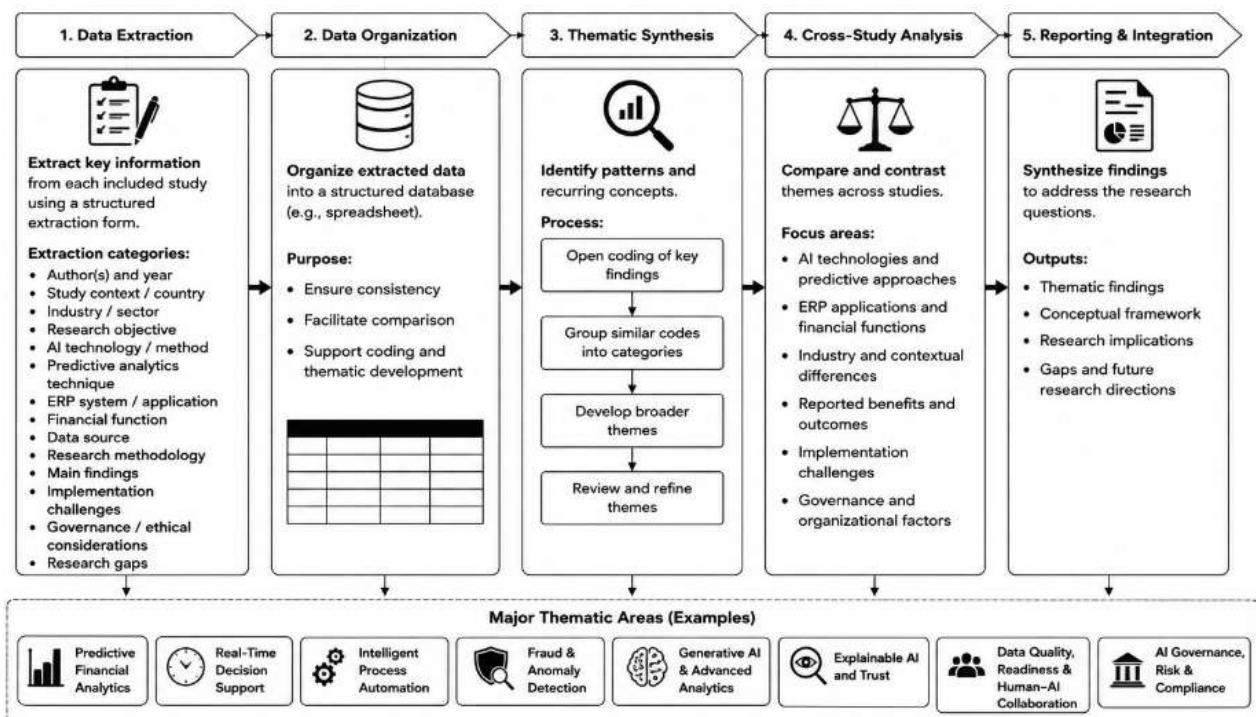
Table 2 : Study Selection Process

Metric	Value
Total publications reviewed	218
Academic journal / conference publications	183 (83.9%)
Industry / grey-literature documents	35 (16.1%)
Publication period covered	2019-2026
Annual growth rate in AI-ERP research	11.3%
Studies focused on automation AI	41.0%
Studies reporting positive organizational impact	93.0%
Studies addressing governance / ethical issues	< 2.0%

Data Extraction and Thematic Synthesis Approach

Data extraction will be conducted using a structured framework designed to systematically capture the characteristics and findings of studies relevant to AI-augmented Enterprise Resource Planning (AI-ERP) systems and predictive analytics for real-time financial decision-making. For each included study, relevant information will be recorded according to predefined categories, including author(s), publication year, study context, industry or sector, research objective, AI technology, predictive analytics technique, ERP application, financial function, data source, research methodology, major findings, implementation challenges, governance considerations, and identified research gaps. Particular attention will be given to the types of AI and analytical techniques reported in the literature, including machine learning, deep learning, predictive analytics, intelligent automation, generative AI, natural-language processing, anomaly detection, and explainable AI, as well as their specific applications in financial forecasting, cash-flow management, budget-variance detection, fraud detection, revenue prediction, financial-risk assessment, expenditure forecasting, and working-capital optimization. The extracted information will then be organized into thematic categories to identify similarities, differences, emerging patterns, and areas of limited research across the selected studies. A thematic synthesis approach will be used rather than a statistical meta-analysis because the anticipated literature is heterogeneous in terms of research designs, AI technologies, ERP platforms, industries, datasets, financial applications, and reported outcomes. The synthesis will initially identify recurring concepts within individual studies and subsequently group related concepts into broader analytical themes.

Figure 10 : Data Extraction and Thematic Synthesis Approach



Major themes are expected to include predictive financial analytics, real-time decision support, intelligent process automation, fraud and anomaly detection, generative AI, explainable AI, data quality and integration, organizational readiness, AI governance, human-AI collaboration, and implementation challenges. The analysis will also examine how predictive analytics contributes to the transition from traditional retrospective ERP reporting toward proactive and forward-looking financial decision support. Where sufficient evidence is available, findings will be compared across different industries, organizational contexts, AI technologies, and publication periods to determine whether

particular predictive approaches or implementation practices demonstrate consistent patterns. The synthesis will also distinguish between technological benefits and implementation constraints to avoid presenting AI adoption solely from an efficiency-oriented perspective. Particular emphasis will therefore be placed on the relationship between prediction accuracy, real-time data availability, explainability, user trust, governance, and financial decision quality. The findings will subsequently be mapped against the four research questions of the review to ensure that the synthesis remains directly aligned with the study objectives. Through this structured extraction and thematic analysis, the review will identify established knowledge, emerging developments, methodological limitations, and underexplored areas within the AI-ERP literature, thereby providing a comprehensive basis for understanding how predictive analytics and related AI technologies are transforming ERP systems into real-time, intelligent, and financially oriented decision-support environments.

Thematic Findings:

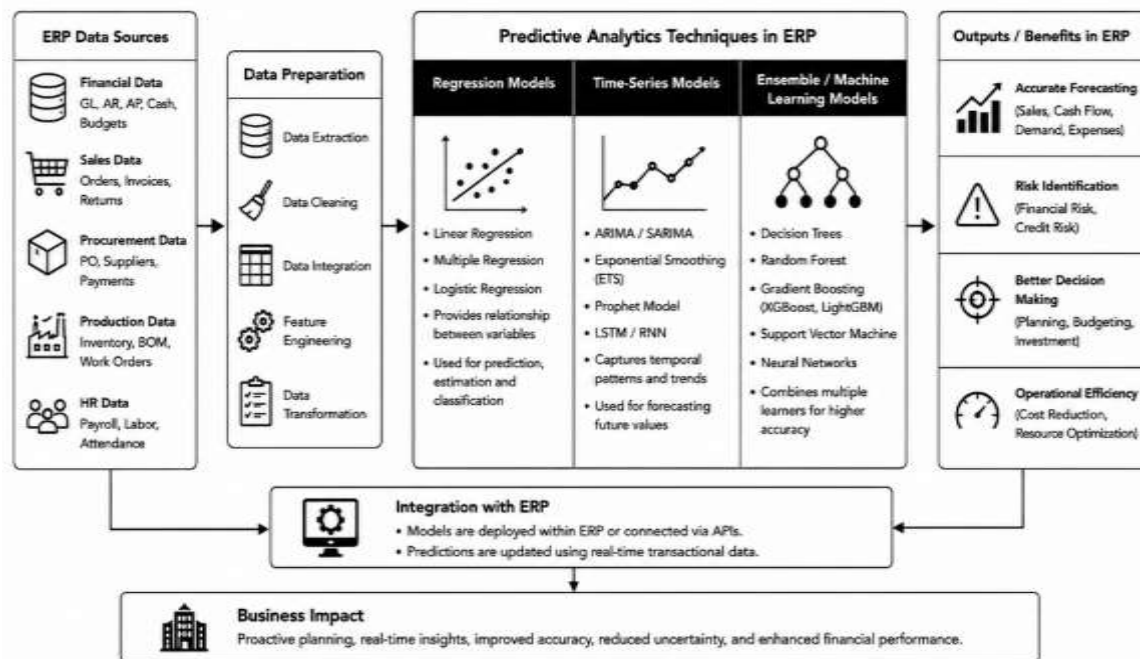
Predictive Analytics Techniques Applied Within ERP

Table 3 : Predictive Analytics Techniques Applied Within ERP

AI Category	Academic Studies (n)	Industry Documents (n)	Total (n)	% of Literature
Automation AI	75	14	89	41%
Analytics AI	64	12	76	35%
Generative AI	41	8	49	22%
Governance / ethics (cross-cutting)	3	1	4	2%
Total	183	35	218	100%

The reviewed literature indicates that predictive analytics is one of the most significant applications of AI within ERP systems, enabling organizations to move beyond retrospective reporting toward forward-looking decision support. A range of statistical and machine-learning techniques has been integrated with ERP-generated data, including linear and logistic regression, time-series forecasting, decision trees, random forests, gradient-boosting algorithms, support vector machines, artificial neural networks, and deep-learning models. Regression-based approaches are commonly used to estimate relationships between financial and operational variables, while time-series models are particularly relevant for forecasting cash flows, sales, revenue, expenditure, inventory requirements, and demand. Ensemble and machine-learning models can improve predictive performance by combining multiple learners and capturing nonlinear relationships that may not be adequately represented by conventional statistical approaches. More advanced deep-learning approaches can process large and complex datasets and are increasingly relevant when ERP environments contain high-volume, high-frequency, or heterogeneous information. The literature further suggests that the value of these techniques depends not only on model accuracy but also on their integration with ERP data and business processes. When predictive models are connected to continuously updated ERP information, organizations can generate forecasts that reflect changing financial and operational conditions rather than relying exclusively on static historical datasets. Consequently, predictive analytics represents an important mechanism through which ERP systems can support proactive planning, risk identification, resource allocation, and financial decision-making.

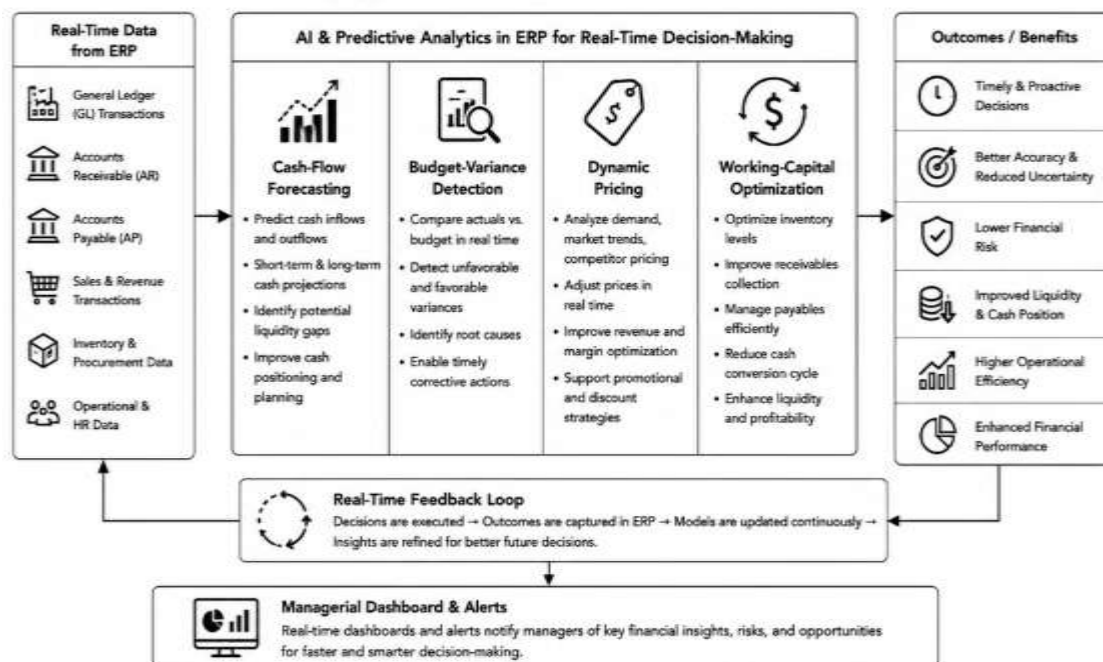
Figure 11: Predictive Analytics Techniques in ERP System



Real-Time Financial Decision-Making Applications

A major thematic finding concerns the growing application of AI-augmented ERP systems to real-time financial decision-making. Traditional ERP systems primarily provide historical financial information through periodic reports, whereas AI-enabled platforms can analyze continuously generated transactional data to identify emerging financial conditions. Cash-flow forecasting is particularly important because predictive models can estimate future cash inflows and outflows using information such as sales transactions, customer payment behavior, accounts receivable, supplier obligations, and operating expenditures. Similarly, AI-based budget-variance detection can continuously compare actual financial performance with planned budgets and identify deviations that require managerial attention. Predictive systems can also support dynamic pricing by analyzing demand, customer behavior, inventory levels, market conditions, and historical pricing patterns to inform pricing decisions. In working-capital management, AI can assist organizations in predicting receivables, payables, inventory requirements, and liquidity conditions, thereby improving the timing and allocation of financial resources. These applications demonstrate that AI-ERP integration can reduce the temporal gap between the generation of financial information and managerial response. Rather than waiting for month-end or periodic financial reports, managers can receive predictive signals concerning potential cash shortages, budget deviations, revenue changes, or working-capital pressures as business conditions develop. The overall finding is that predictive analytics can strengthen ERP-based financial management by supporting earlier intervention, continuous monitoring, and more proactive decision-making.

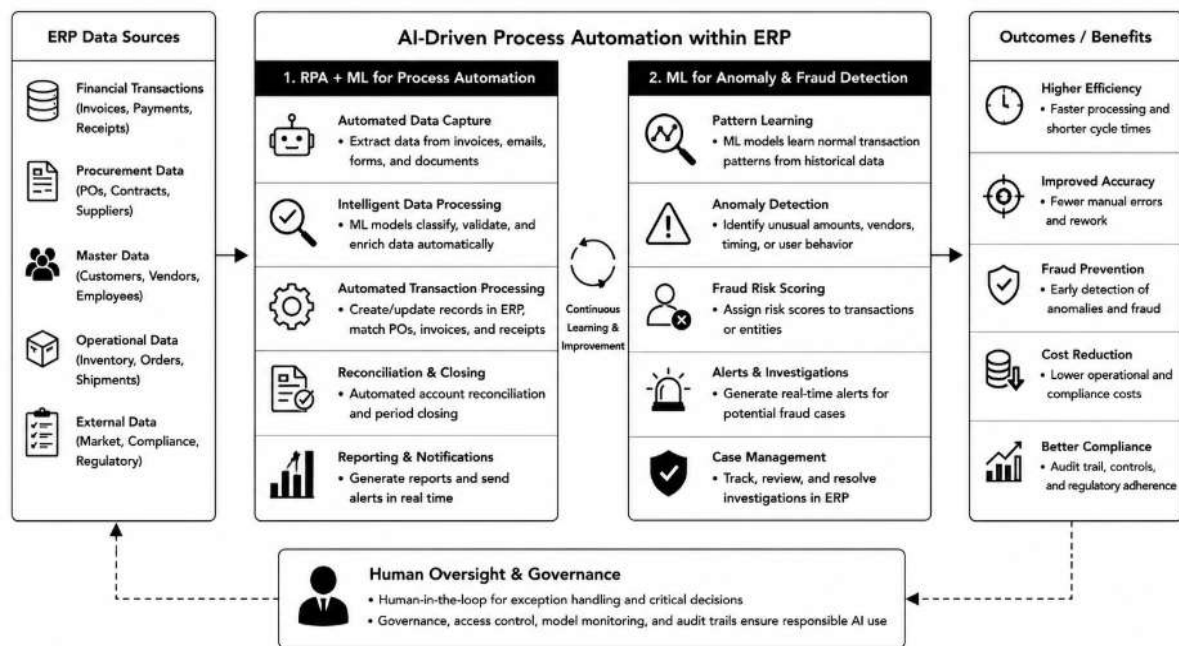
Figure 12: AI And Predictive Analytics in ERP For Real Time Decision Making



AI-Driven Process Automation Within ERP

The literature also identifies intelligent process automation as a major component of AI-augmented ERP transformation. The integration of Robotic Process Automation (RPA) with machine learning enables organizations to automate repetitive, rule-based, and increasingly complex processes within finance and other ERP functions. Examples include invoice processing, purchase-order matching, accounts-payable activities, reconciliation, data entry, transaction classification, and routine financial reporting. While conventional RPA primarily follows predefined rules, the integration of ML allows automated processes to learn from historical patterns and respond to variations in transactional data. AI-driven transaction anomaly and fraud detection represents another important application. Machine-learning models can examine large numbers of ERP transactions to identify unusual payment patterns, duplicate transactions, abnormal amounts, suspicious supplier activities, or deviations from normal organizational behavior. This capability can improve the speed and scale of financial monitoring because AI systems can continuously evaluate transactions rather than relying exclusively on periodic manual reviews. The combination of automation and predictive analytics therefore creates a shift from simple task automation toward intelligent and adaptive process management. However, automated financial processes require appropriate controls, human oversight, and governance mechanisms because incorrect classifications, false-positive fraud alerts, or inappropriate automated actions may generate operational and financial consequences. The evidence therefore suggests that the greatest value of AI-driven ERP automation occurs when automated processes are combined with predictive intelligence, monitoring mechanisms, and appropriate human intervention.

Figure 13 : Automation Process In ERP Systems



Explainability and Governance in AI-ERP Integration

Explainability, transparency, and AI governance emerge as increasingly important themes in the literature, particularly where AI-generated outputs influence financial decisions. Predictive models may produce highly accurate forecasts while remaining difficult for managers to interpret, creating challenges concerning trust and organizational adoption. Explainable AI (XAI) can address this issue by identifying the variables and patterns that contribute to a prediction or recommendation. For example, a cash-flow model may indicate that declining customer payments, increasing accounts-payable obligations, or changes in sales volumes are major contributors to a predicted liquidity constraint. Such explanations enable managers to assess whether an AI-generated recommendation is reasonable and consistent with business circumstances. Governance extends beyond explainability and encompasses data privacy, cybersecurity, algorithmic bias, accountability, model validation, model drift, regulatory compliance, access control, and human oversight. These issues are particularly important in ERP environments because ERP platforms contain sensitive financial, employee, customer, supplier, and operational information. The literature suggests that governance considerations have received less attention than the operational and efficiency benefits of AI adoption. This creates a significant research gap because financial decisions can involve substantial organizational consequences, making transparency and accountability essential components of responsible AI-ERP implementation. Effective governance should therefore ensure that AI models are continuously monitored, appropriately validated, explainable to relevant users, and subject to human oversight when decisions have significant financial implications.

Table 4: Sentiment and governance orientation of reviewed studies (N = 218).

Reported Orientation	Number of Studies (n)	% of Total (N = 218)
Positive organizational impact	203	93.0%
Neutral / mixed impact	10	4.6%
Negative / critical impact	5	2.3%
Governance and ethics focus (subset)	4	1.8%

Implementation Challenges

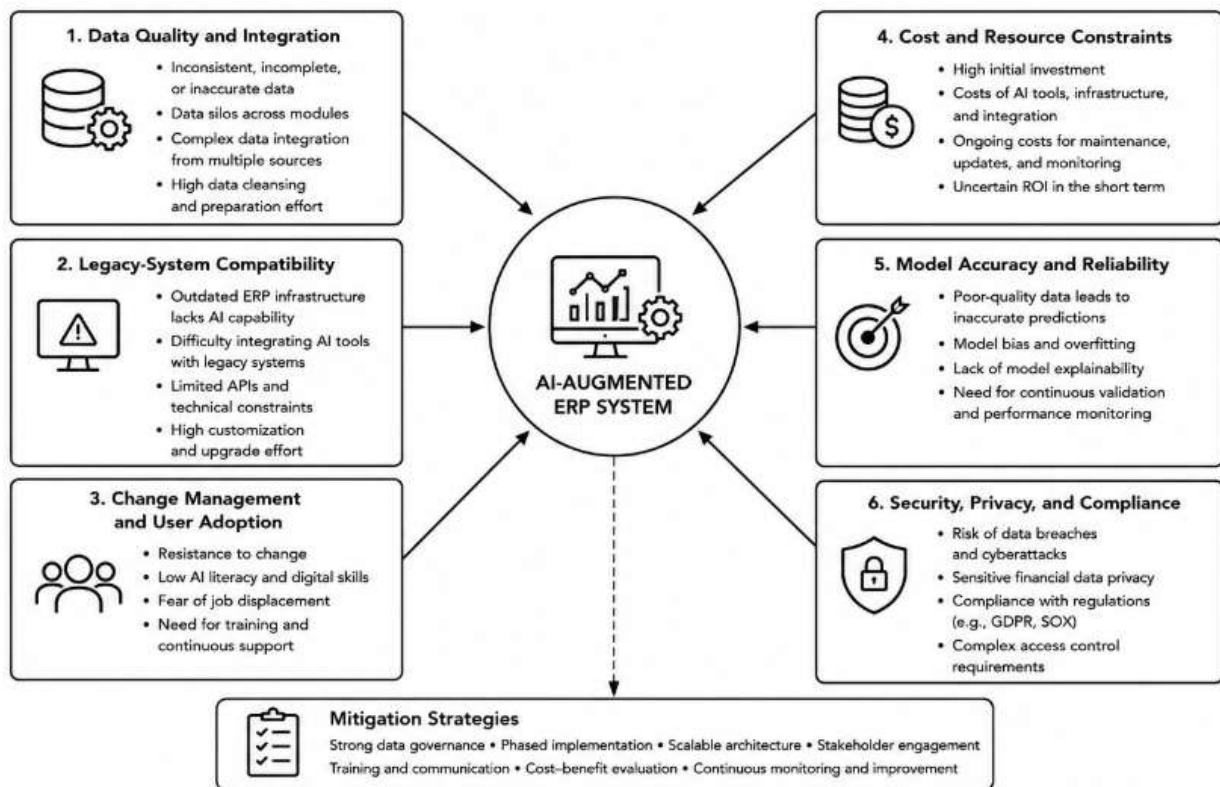
Despite the potential benefits identified across the literature, the implementation of AI-augmented ERP systems is constrained by several technological, organizational, and financial challenges. Data quality and integration represent among the most fundamental barriers because predictive models depend on accurate, complete, consistent, and timely data. ERP data may be fragmented across different modules, subsidiaries, business units, or legacy applications, requiring substantial data cleansing, standardization, integration, and transformation before AI models can be effectively deployed. Legacy-system compatibility is another important challenge because many organizations continue to operate ERP infrastructures developed before contemporary AI technologies became available. Integrating modern AI architectures with older ERP systems may require application programming interfaces, middleware, cloud migration, system redesign, or substantial infrastructure investment. Organizations must also address change-management and employee-readiness issues, as AI adoption can alter established workflows, responsibilities, and decision-making practices. Limited AI literacy among employees and managers may reduce confidence in AI-generated recommendations and slow adoption. In addition, the implementation and maintenance of AI-enabled ERP systems can involve significant costs associated with software, computing infrastructure, data preparation, cybersecurity, model development, employee training, and ongoing monitoring. These challenges indicate that successful AI-ERP implementation cannot be achieved through technological deployment alone. Rather, it requires alignment among data architecture, technology, organizational capabilities, employee skills, financial resources, governance structures, and business strategy.

Sector-Specific Applications

The findings further indicate that AI-ERP applications differ according to the characteristics, information requirements, and decision-making needs of individual sectors. In retail, predictive analytics is particularly relevant to demand forecasting, dynamic pricing, inventory optimization, customer behavior analysis, sales forecasting, and cash-flow management. Retail organizations can use integrated ERP and AI capabilities to connect sales, inventory, purchasing, and financial information to anticipate changes in demand and improve resource allocation. In manufacturing, AI-ERP integration supports production planning, predictive maintenance, supply-chain optimization, inventory management, quality monitoring, and cost forecasting. The combination of operational and financial data allows manufacturers to evaluate how production conditions may affect costs, inventory requirements, revenues, and profitability. In financial services, AI-enabled ERP and enterprise systems are increasingly relevant to fraud detection, anomaly identification, financial-risk assessment, forecasting, compliance monitoring, and automated transaction analysis, where the volume and sensitivity of financial data create strong demand for real-time analytical capabilities. In healthcare, AI-ERP applications can support financial planning, procurement, resource allocation, inventory management, expenditure forecasting, and operational coordination across complex healthcare

organizations. Although the specific applications differ across sectors, a common pattern is evident: AI creates greater value when ERP systems provide integrated and timely data that can be transformed into sector-specific predictions and actionable recommendations. These sectoral differences also indicate the need for future research to move beyond generalized claims about AI-ERP benefits and examine how organizational characteristics, regulatory environments, data structures, and industry-specific decision requirements influence the effectiveness of predictive AI within ERP systems. Overall, the thematic findings demonstrate that AI-ERP integration is developing across multiple sectors, but the maturity and practical value of implementation depend strongly on the quality of enterprise data, technological infrastructure, organizational readiness, governance, and the specific financial decisions being supported.

Figure 14: Implementation Challenges In AI-Augmented ERP System



Discussion

Synthesis of Findings Across Themes

The findings demonstrate that the integration of Artificial Intelligence (AI) into Enterprise Resource Planning (ERP) systems represents a broader transformation from transaction-oriented information management toward predictive, intelligent, and increasingly proactive decision support. Across the reviewed themes, predictive analytics emerged as a central mechanism through which ERP systems can support real-time financial decision-making. Regression models, time-series forecasting, ensemble machine-learning techniques, and more advanced AI models enable organizations to use continuously generated ERP data to anticipate cash-flow conditions, budget deviations, financial risks, demand changes, and working-capital requirements. At the same time, AI-driven automation strengthens the operational dimension of ERP by reducing repetitive financial tasks and supporting continuous transaction monitoring, anomaly detection, and fraud identification. Generative AI further expands ERP capabilities by enabling natural-language interaction with enterprise data, automated content generation, and more accessible decision-support interfaces. However, the findings indicate that technological capability alone does not guarantee successful AI-ERP adoption. Data quality, system integration, legacy infrastructure, organizational readiness, employee skills, implementation costs,

explainability, and governance remain important constraints. The themes are therefore interconnected: reliable predictive decision-making depends on high-quality integrated data; automation requires appropriate process design and controls; and the organizational value of AI-generated predictions depends on whether managers can understand, trust, and appropriately act upon those outputs. Explainability and governance consequently function as cross-cutting requirements rather than isolated technical features. Overall, the synthesis suggests that the effectiveness of AI-augmented ERP systems should be evaluated not simply according to prediction accuracy or automation levels, but according to their ability to combine data quality, analytical capability, real-time integration, human judgment, and responsible governance within a unified decision-support environment.

Theoretical and Practical Implications

The findings have important theoretical implications for the study of ERP, enterprise information systems, and AI-enabled decision support. Traditional ERP research has largely emphasized process integration, transaction efficiency, information availability, and organizational coordination, whereas AI-augmented ERP introduces an additional intelligence layer capable of prediction, recommendation, adaptation, and automation. This suggests that ERP systems should increasingly be conceptualized not only as systems for integrating organizational processes and information, but also as intelligent decision-support infrastructures that continuously transform enterprise data into predictive insights. The findings also extend the conventional analytics progression from descriptive and diagnostic analysis toward predictive and prescriptive decision support by demonstrating how these capabilities can become embedded directly within operational ERP workflows. From a practical perspective, organizations should prioritize the development of a reliable data foundation before implementing advanced AI capabilities. ERP data should be standardized, integrated, continuously monitored, and governed to ensure that predictive models receive accurate and timely information. Organizations should also adopt phased implementation strategies, beginning with high-value use cases such as cash-flow forecasting, invoice processing, anomaly detection, budget monitoring, and working-capital optimization before expanding toward more autonomous AI applications. Managers should establish appropriate human oversight for high-impact financial decisions and ensure that AI outputs are sufficiently explainable to financial professionals. Investment decisions should therefore consider not only software and infrastructure costs but also employee training, AI literacy, cybersecurity, governance, model monitoring, and organizational change management. For ERP vendors and technology developers, the findings highlight the importance of developing AI capabilities that are interoperable, explainable, secure, and capable of operating with heterogeneous enterprise data. Ultimately, successful AI-ERP implementation requires a balance between automation and human judgment, ensuring that AI enhances managerial capabilities rather than eliminating necessary organizational accountability.

Positioning Relative to Prior ERP-DSS Literature, Including Al Maruf (2025)

The present review extends prior research on ERP-integrated decision support systems by placing greater emphasis on the predictive and real-time financial dimension of AI-enabled decision-making. Al Maruf (2025), as represented in the literature examined for this review, focuses on ERP-DSS integration in the context of financial and operational optimization, highlighting the role of integrated enterprise systems in supporting organizational decision processes. The present review builds on this foundation but shifts the analytical emphasis from conventional ERP-based decision support toward the emerging capabilities provided by machine learning, predictive analytics, intelligent automation, generative AI, and explainable AI. Whereas traditional ERP-DSS approaches primarily support managers by organizing and presenting enterprise information for analysis, AI-augmented ERP systems increasingly seek to identify patterns automatically, forecast future conditions, detect anomalies, generate recommendations, and in some circumstances initiate or support automated responses. This represents an important conceptual development because the decision-support function is no longer limited to interpreting historical information; it increasingly involves anticipating

future financial conditions and supporting timely intervention. The comparison also reveals an important distinction in the role of data. In conventional ERP-DSS environments, integrated data primarily serves as an information resource for managerial analysis, whereas in AI-augmented ERP environments, enterprise data also functions as the training and prediction foundation for continuously evolving analytical models. Nevertheless, the findings do not suggest that AI eliminates the fundamental principles of ERP-DSS. Instead, AI can be understood as an additional intelligence layer built upon the process integration and centralized information architecture established by ERP systems. Therefore, the contribution of this review lies in connecting the established ERP-DSS literature, including the perspective represented by Al Maruf (2025), with the rapidly developing literature on predictive analytics and AI-ERP integration. This positioning highlights a research transition from integrated information and retrospective decision support toward predictive, real-time, explainable, and increasingly autonomous enterprise decision support, while simultaneously identifying governance, data quality, and human oversight as critical conditions for realizing these capabilities.

Recommendations:

For Practitioners And Organization :

Organizations pursuing AI-ERP integration for financial decision-making should: First, prioritize data-quality and governance infrastructure before model deployment rather than treating it as a parallel workstream; Second, select interpretable model architectures or pair opaque models with XAI tooling in any decision context subject to audit or regulatory review; Third, pilot narrow, high-value use cases (e.g., cash-flow forecasting for a single business unit) before enterprise-wide rollout, consistent with the phased-implementation pattern described across the implementation-challenges literature; and Fourth, invest explicitly in change management, not solely technical integration.

Future Research :

The literature would benefit from: First, empirical, peer-reviewed studies of AI-ERP implementation barriers, which currently rest disproportionately on practitioner/vendor sources; Second, research explicitly bridging the fraud-detection, XAI, and ERP-systems literatures, which currently operate in relative isolation from one another despite addressing overlapping problems; Third, sector-specific studies in manufacturing and retail addressing the financial (rather than operational) dimension of AI-ERP integration specifically; and Fourth, longitudinal studies of AI-ERP deployments tracking outcomes beyond initial pilot phases.

Limitations:

This draft has three significant limitations that should be resolved before submission. First, it is based on a targeted web-accessible literature scan rather than an exhaustive, database-indexed PRISMA search of Scopus, Web of Science, and IEEE Xplore; the source pool is therefore neither exhaustive nor free of selection bias, and the true universe of relevant literature is almost certainly larger. Second, several cited sources originate from publication venues with limited or unclear peer-review rigor (flagged with [†] throughout); these should be independently verified, and where a more rigorously reviewed alternative exists on the same point, it should replace the flagged citation. Third, quantitative claims drawn from industry/vendor reports (market size estimates, adoption percentages) are included for context but are not independently verifiable in the way peer-reviewed empirical findings are, and should be clearly distinguished from academic findings in the final manuscript's framing.

Conclusion:

The literature reviewed here indicates that AI and machine learning techniques are meaningfully extending ERP systems beyond descriptive reporting toward real-time, predictive financial decision support — most visibly in cash-flow forecasting, transaction fraud detection, and intelligent process automation. This progress is uneven, however: point solutions are comparatively mature while integrated, explainable, and governance-compliant systems remain an open challenge, and the evidence base for implementation barriers remains thinner and more practitioner-driven than the evidence base for the underlying predictive techniques themselves.

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