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Integrating Artificial Intelligence and Enterprise Resource Planning Systems: A Structured Review of Decision Support Capabilities, Constraints, and Governance

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ABSTRACT

This review paper examines the integration of artificial intelligence (AI) into enterprise resource planning (ERP) systems to support real-time, evidence-based decision-making across core business functions. The study draws on a structured review of peer-reviewed and standards-based sources published between 2020 and 2025. It considers how AI techniques, including machine learning, predictive analytics, anomaly detection, and explainable AI, enhance ERP-enabled planning, control, and performance management in finance, procurement, manufacturing, and supply chain operations. The review identifies enabling conditions for value realization, such as data governance, process standardization, and change management, as well as constraints related to model risk, bias, privacy, and organizational readiness. Management findings are interpreted through socio-technical systems and resource-based perspectives, with emphasis on the point that durable benefits depend on the co-evolution of technology, people, and process capabilities.

1. Introduction

Enterprise Resource Planning (ERP) systems have served as foundational platforms for integrating core business functions, finance, procurement, manufacturing, human resources, and sales into unified data architectures that support operational visibility and process standardization. Historically, ERP evolved from material requirements planning (MRP) and manufacturing resource planning (MRP II) systems that emerged in the 1960s and 1970s, with the term "enterprise resource planning" gaining prominence in the early 1990s to describe broader, enterprise-wide integration beyond the manufacturing domain [1,2]. Contemporary ERP platforms are expected not merely to record transactions but to enable faster sensing, forecasting, and decision cycles [3,4]. Recent waves of digital transformation, accelerated by cloud delivery models, standardized APIs, and embedded analytics, have expanded the role of ERP from back-office infrastructure to a strategic decision-

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support platform [1,3]. Cloud ERP architectures provide elastic compute, continuous feature updates, and integration readiness that are increasingly important prerequisites for operationalizing artificial intelligence (AI) at scale [4,5]. As organizations generate ever-larger volumes of transactional and operational data, the limitations of manual analysis and rule-based decision-making become more pronounced, creating demand for intelligent systems capable of processing complex, high-dimensional data in near real time. The period from 2020 to 2025 has been particularly consequential: cloud ERP adoption accelerated, embedded AI capabilities became standard vendor offerings, and regulatory frameworks for algorithmic accountability began to take shape, creating both new opportunities and obligations for organizations deploying AI in enterprise systems [5,6].

The integration of AI into ERP systems represents a paradigm shift in organizational decision-making (Figure 1). AI, defined broadly as systems designed to perform tasks that typically require human intelligence, including learning, reasoning, and self-correction [7], encompasses techniques such as machine learning (ML), natural language processing (NLP), predictive analytics, and anomaly detection that enable ERP platforms to move beyond descriptive reporting toward predictive and prescriptive capabilities [7,8].

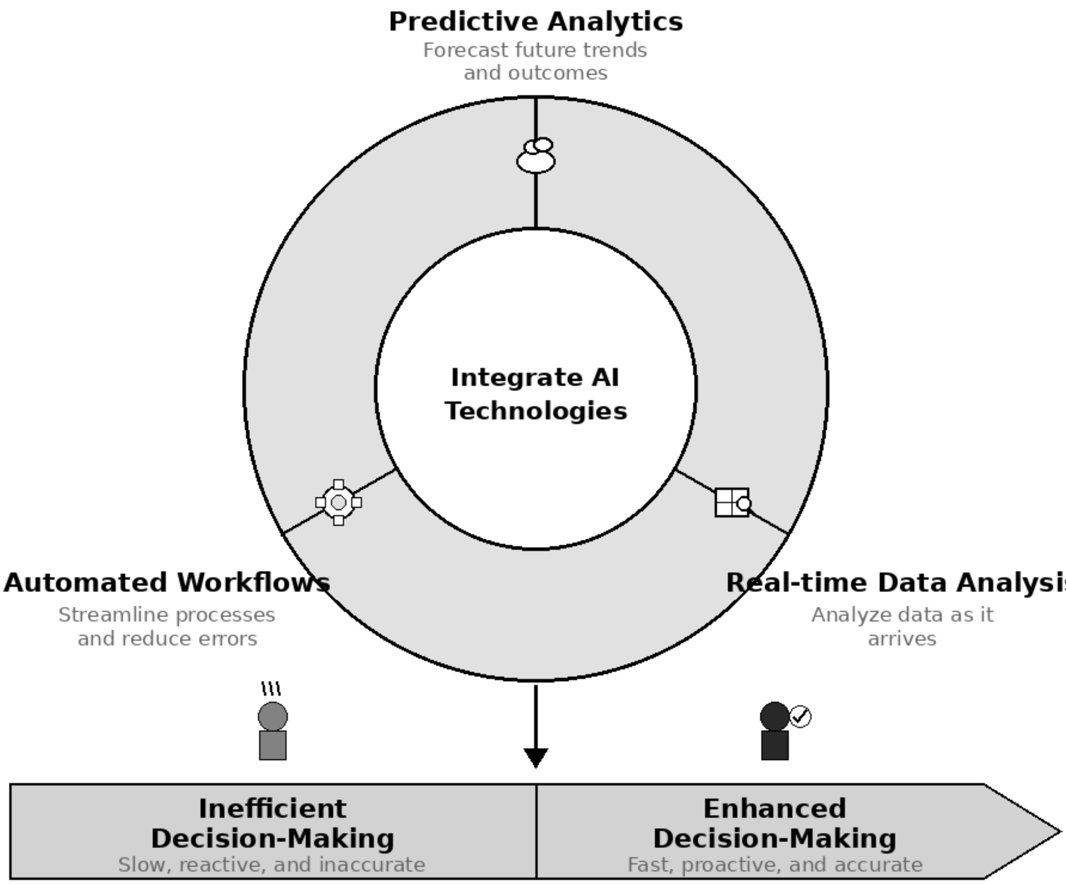

Fig. 1. AI-enabled ERP decision-making: Transforming inefficient to enhanced outcomes through the integration of predictive analytics, automated workflows, and real-time data analysis

ML allows ERP systems to identify demand patterns, optimize inventory replenishment, and forecast financial outcomes by training on historical transactional data [8]. NLP extends ERP utility by extracting actionable signals from unstructured data sources such as customer feedback, service tickets, and social media content; while ERP-specific NLP evidence remains limited, the broader enterprise systems literature documents consistent gains from unstructured data integration [3,9]. Predictive analytics supports proactive risk management, enabling organizations to anticipate supply chain disruptions, detect anomalous financial transactions, and plan capacity adjustments before problems materialize [9,10].

Despite these potential benefits, AI-ERP integration introduces significant challenges. Organizations face technical hurdles related to data quality, system compatibility, and infrastructure readiness [11]. Technical challenges include integration complexity, data quality, and security issues, alongside the need for specific AI and data science skills, which are often in short supply [7,11]. Organizational challenges comprise resistance by employees to adopting new technologies, the lack of skills in AI and data science, and the high costs of implementing AI solutions, which may be a barrier for small and medium-sized enterprises [11,12]. In addition, there are ethical challenges related to the transparency, fairness, and accountability of AI-based decision-making, which are particularly relevant in regulated environments, such as financial and HRM applications [13,14].

Systematic reviews of the literature on AI in the context of supply chain management [9,15] and the adoption of analytics in ERP systems [16] have previously been published. However, there are three knowledge gaps that this systematic review aims to address. First, previous reviews have considered AI techniques in isolation and have not discussed how techniques are associated with specific ERP-supported decision-making areas (e.g., inventory management, financial management, HRM, and procurement management). Second, most of the reviews have not explicitly considered the availability of governance and ethics as enablers for realizing the value of AI in conjunction with the technical enablers. Finally, most of the reviews have employed a single theoretical perspective. This review addresses these three gaps by providing a systematic review of the recent academic literature that associates AI techniques with specific decision-making areas supported by ERP systems and by employing three theoretical perspectives, namely, the socio-technical systems theory, the resource-based view, and the Technology-Organization-Environment model to analyze how technical, organizational, and environmental factors affect AI-enabled decision making in ERP systems.

1.1 Theoretical Framework

This systematic review employs three theoretical perspectives: the socio-technical systems theory, the resource-based view, and the technology-organization-environment model. Socio-technical systems theory is used as the main theoretical perspective for guiding this systematic review. This theory posits that an information system, such as an ERP system, is a socio-technical entity that consists of a technical subsystem (e.g., data management, business rules management, and user interface management) and a social subsystem (e.g., skills, culture, and structure) that are linked by shared processes [17]. The resource-based view is used as a secondary perspective for explaining the ability of organizations to achieve competitive advantages through AI adoption. This theory posits that competitive advantage is achieved when resources are valuable, rare, and costly to imitate [18]. Therefore, this theory can be employed to analyze the literature to identify which resources (e.g., AI techniques, data, analytics skills, and governance) are associated with the ability of organizations to leverage AI to achieve competitive advantages in their decision-making processes. Finally, the technology-organization-environment model is used as another secondary perspective for analyzing three contexts (technological, organizational, and environmental) that affect the adoption and implementation of technological innovations, such as AI, in organizations [19]. In addition, we will use the information systems success model as an evaluation perspective for assessing the success of AI-enabled ERP systems. This model consists of four dimensions, namely, system quality, information quality, service quality, and net benefits [10].

1.2 Research Questions

The objective of this systematic review is addressed through three research questions:

i. How does AI affect the decision-making processes supported by ERP systems?
ii. What AI techniques (e.g., ML, NLP, predictive analytics) are being used in or with ERP systems, and what decision-making functionalities do they support?
iii. What technical, organizational, cost-related, and ethical concerns need to be addressed when integrating AI into ERP systems?

The knowledge gap that this review aims to address is the lack of a theoretically-informed systematic review of academic literature on the integration of AI techniques into or with specific ERP-supported decision-making areas while considering technical, organizational, cost-related, and ethical enablers. This review aims to address this knowledge gap by providing a systematic review of recent academic literature (2020-2025) on AI-enabled decision-making in ERP systems.

2. Methodology

This qualitative structured review and comparative case study aims to assess how AI enhances decision-making in the context of ERP systems. The structured review is used to analyze the current peer-reviewed and standards-based literature, highlighting the most commonly used AI techniques and their contributions to decision-making in different areas of ERP systems. The research questions are addressed through a combination of thematic synthesis and cross-case analysis.

2.1 Search Strategy and Data Collection

The literature search was conducted in Google Scholar, IEEE Xplore, and Science Direct. In addition, some high-credibility standards and regulatory sources (e.g., ISO/IEC standards, NIST, OECD, EU regulations) were used. In addition, search queries such as "AI" AND "ERP", "machine learning" AND "enterprise resource planning", "decision support" AND "ERP", and "predictive analytics" AND "ERP" were used. Besides, the reference lists of highly cited papers were also consulted to consider additional literature. The time filters considered were 2020 to 2025, although some classical papers were also included (e.g., historical overviews of ERP, conceptual frameworks), in case they were still relevant. The literature search resulted in approximately 210 records in the three databases. After removing duplicates, titles and abstracts were screened, and 89 full-text papers were further evaluated. After this screening, 32 peer-reviewed and standards-based articles were included. Standards documents and regulatory frameworks (n=9) were considered separately because of their relevance to governance. It is important to clarify that standards-based articles were only used to discuss governance, risk management, and ethical issues, and not as evidence of AI performance, as is done throughout the rest of the paper.

2.2 Inclusion and Exclusion Criteria

The inclusion criteria used were:

i. empirical or review articles dealing with AI techniques in the context of ERP;

ii. direct relation to decision-making (forecasting, inventory optimization, risk scoring, process automation);
iii. papers published in peer-reviewed scientific journals, proceedings, or standards bodies.

Papers with no scientific content, papers without enough information about the methodology, or those that were not related to decision-making in the context of ERP were excluded. However, policy and standards documents (ISO/IEC, NIST, OECD, EU) were included because of their relevance to governance.

2.3 Analytical Approach

The analysis of the selected articles was based on a thematic coding approach. The evidence of the included articles was coded according to categories related to the objective of this study: decision automation, predictive accuracy, real-time responsiveness, and implementation constraints. A technology-to-decision mapping approach was used to categorize the evidence according to the AI technique used (ML, predictive analytics, NLP) and the type of ERP decision affected (inventory and supply chain, financial planning and risk, workforce and customer-facing decisions). The evidence was compared between articles and cases to discuss the patterns and differences, which helped identify patterns and differences of the benefits, limitations, and practical implications of AI-enabled decision-making in the context of ERP. The four illustrative cases used (Walmart, Siemens, General Electric and IBM) were selected to show the use of AI in the context of ERP across industries and across different business functions (inventory management, financial planning, predictive maintenance, HR analytics). These cases were not selected with the purpose of being representative. The criteria for choosing these cases were:

i. be frequently cited in the AI–ERP literature;
ii. be from different industries and cover different aspects of ERP functionalities;
iii. have outcomes documented in credible sources.

2.4 Methodological Transparency and Limitations

The screening and coding of the papers were conducted by a single author; this is a common limitation in a structured review that lacks a second coder. In order to minimize selection bias, the inclusion and exclusion criteria were applied consistently to all records, and a reflexivity check was performed by re-examining the borderline papers against the research questions before making a final inclusion or exclusion decision. The screening process follows the reporting format adopted from the Preferred Reporting Items for systematic reviews and meta-analyses (PRISMA) [20]. The review covers only papers written in English and published between 2020 and 2025 (except for a few highly influential prior studies), which might exclude relevant empirical studies published in non-English languages or industry reports that are not indexed in the searched databases. The generalizability of the findings is also limited by the restriction to academic and standards-based sources, which might trail the practice in some fast-developing areas of AI applications.

3. Results

In this section, the results are presented according to three main themes: AI technologies and their decision-support roles in ERP systems, the benefits and value creation of AI-enabled ERP, and the challenges and risks associated with AI-enabled ERP. A case analysis of several organizations is also presented to show the results of AI-enabled ERP in practice.

3.1 AI Technologies and ERP Decision Domains

3.1.1 Machine learning in inventory and supply chain decisions

The literature reveals that one of the key AI technologies that can be integrated with an ERP system is ML. The integration of an ML model into an ERP system can change the traditional use of the system from descriptive analytics to predictive and prescriptive analytics [9,15]. The ML model can learn from the data stored in an ERP system, e.g., sales orders, lead times of suppliers, movements of stock, and production plans, in order to predict the future and provide prescriptions for inventory and supply chain management decisions [9,15]. Some of the key contributions of ML to inventory and supply chain management decisions include making accurate demand forecasts, which helps reduce stockouts and overstocking, making quick responses to changes in demand or seasonalities, and setting up an inventory policy that is improved with time as new data are collected [9,21]. However, the results of an ML model can be only as good as the data used for learning, and, in an ERP environment, the integration of the data across different modules, the data quality, and the availability of the data are key factors that determine the success of an ML model [9]. Poor data integration and quality can affect the learning process of an ML model, leading to low-quality results that are difficult to implement [13]. In addition, the results of an ML model can be particularly valuable in organizations with mature data governance and business process standardization [12,22].

3.1.2 Predictive analytics in financial forecasting and risk management

Predictive analytics is another AI technology that has a key role in an ERP environment. Existing enterprise system literature indicates that AI-based forecasting has a positive relationship with the ability to predict changes in demand, optimize inventory levels, and reduce stock-outs [9,10]. Predictive and prescriptive analytics can support the making of better capacity plans by providing recommendations based on historical data and other external data, which improves planning key performance indicators (KPIs) and service level [9,10]. In the financial planning process, predictive analytics can support proactive financial decisions by providing accurate financial forecasts that support better budgeting choices, early identification of potential cost escalation, and better working capital management by predicting the changes in accounts receivable, accounts payable, and inventory holding costs [22,23]. In addition, predictive analytics can support financial risk management by identifying unusual transaction patterns, which supports the design of internal control and fraud detection [10,24]. Although the benefits of using predictive analytics are described above, in the literature, the following operational risks are discussed:

i. predictions can be sensitive to abrupt structural changes (e.g., economic crisis or change in policies);
ii. overconfidence in predictions.

Consequently, there is an increasing body of literature that highlights the need for explainability, risk management, and human oversight in predictive modeling for effective and ethical use of AI in financial planning [7].

3.1.3 Natural language processing and unstructured data in ERP decisions

NLP can be used to extract insights from unstructured data such as emails, service requests, recorded conversations, and social media posts. These insights can be used for sentiment-based demand forecasting and exception handling [9]. It is likely that, in practice, the need for an additional data processing and storage platform (i.e., data lake or data lakehouse) will arise, as the traditional databases in ERP are designed for structured relational data processing. The results of AI/ML predictions can be integrated with the master data of an ERP system and presented in an analytics-based user interface to support operational decision-making. In customer-centric business functions, NLP facilitates fast decision-making by identifying common service issues, escalation criteria, and product issues that are not captured in structured data. In HRM, NLP-based candidate screening and document processing facilitate recruitment processes, employee request handling, and employee sentiment analysis to increase the speed and consistency of HR decisions [8]. The literature characterizes the value of NLP as decision comprehensiveness: decision-makers can include qualitative data (i.e., text and voice) in their decision-making to complement structured data captured in ERP systems [13]. However, the application of NLP in an ERP environment poses a high level of risk:

i. the text and voice data may be noisy and context-dependent, especially when they are captured through informal communication. Furthermore, they may be biased;
ii. privacy and security risks are high, as unstructured data often contains personally identifiable information (PII) and sensitive business data.

Therefore, companies should implement strong data protection, data minimization, and ethical use of data practices to mitigate the risks [13,25].

3.2 Enablers, Constraints, and Governance

In the literature, three enablers are identified for AI adoption in ERP systems:

i. data management and master data quality;
ii. cloud and integration maturity to support continuous deployment;
iii. change management to adapt the organization to new automation capabilities.

The principles of change management are discussed in [26]. The findings of this study are supported by recent literature on AI adoption in enterprises, which points out that this is one of the main challenges to AI adoption [12,27]. On the other hand, the constraints are mostly related to model risk: biased or unstable models can generate massive errors when they are integrated with ERP operations. The risk is higher when AI is used in critical business functions such as financial planning and HRM [14,28]. The literature calls for risk management practices, model robustness, explainability, and transparency [29]. The results are in line with recent studies on AI risk management, which discuss the available frameworks, standards, and practices [30,31].

3.3 Benefits of AI-Enhanced ERP Decision-Making

The analysis of literature suggests that the integration of AI in ERP systems is likely to have the following benefits:

i. to reduce the need for human labor for repetitive decision-making, such as in inventory replenishment, invoice matching, and production scheduling, and to enable the employee to focus on more important tasks [8,9];
ii. to enhance the accuracy of decision-making with the help of ML algorithms to process large data and to identify patterns which may not be possible for humans to recognize [8,21];

iii. to enable real-time decision-making to manage disruption in supply chain, financial fraud, and market changes [9,10];
iv. to facilitate strategic decision-making through simulation, scenario planning, and predictive analytics to evaluate the outcomes of a decision before taking the action [8,16].

The aforementioned capabilities can be considered as valuable resources for a firm when they are embedded in the firm-specific ERPs and business processes, as suggested by resource-based theory [18] and demonstrated in recent studies on enterprise AI [3,21]. The summary of key sources and their contributions is given in Table 1.

Table 1
Summary of key sources and their contributions to AI–ERP decision-making

Source	Focus area	Key contributions
Christiansen *et al.* [4]	Cloud ERP adoption	Identifies organizational and technical factors shaping cloud ERP adoption; implications for AI scalability.
Toorajipour *et al.* [9]	AI in supply chain	Systematic review of AI applications in supply chain management; maps ML techniques to demand sensing and logistics.
Dziembek & Turek [11]	AI–ERP integration models	Proposes integration architecture for embedding AI services into ERP; emphasizes interoperability and monitoring.
Butarbutar *et al.* [12]	ERP post-implementation CSFs	Identifies critical success factors for sustained ERP value; emphasizes change management and continuous improvement.
Arrieta *et al.* [13]	Explainable AI (XAI)	Synthesizes XAI concepts and taxonomies; links explainability to trust, compliance, and oversight in ERP workflows.
Solano & Cruz [16]	Analytics integration in ERP	Systematic review of how embedded analytics impacts ERP decision quality; identifies innovation patterns across modules.

AI also raises issues such as governance, trustworthiness, and ethics of decision-making. The key challenges include a lack of transparency in AI-based models, data privacy, biased recommendations, and over-automation of decision-making [24,28]. Therefore, it is essential to validate the AI models, to continuously monitor the performance of the models, and to establish the accountability and responsibility of AI-based decision-making.

3.4 Implementation Challenges
3.4.1 Technical challenges

Data integration is one of the major technical challenges for integrating AI in ERPs. An ERP system deals with a large amount of structured and unstructured data collected from different sources. It is essential to ensure the quality of the data and to preprocess the data to make it suitable for use in AI algorithms, which is time-consuming and costly. The integration of AI applications with existing ERPs requires high levels of technical skills and may demand significant investment in IT infrastructure [5,11]. Another technical issue is concept drift, which refers to the decrease in the performance of ML models over time due to changes in data distribution. This issue can be managed with the help of model management strategies such as model versioning, retraining of the model from time to time, and detecting concept drift [32]. These technical issues highlight that, from the perspective of socio-technical systems theory [3,17], the technical systems (e.g., AI algorithms) alone cannot ensure the effectiveness of AI-based ERPs. Rather, the social systems, including data management, business process, and decision-making process, should be aligned with the technical systems to ensure the reliability of AI-based ERPs.

3.4.2 Organizational and cost challenges

From an organizational perspective, resistance to change is a common issue when implementing AI in ERPs. Employees may not accept the change due to fear of losing their jobs or due to a lack of confidence in using AI technologies. Moreover, there is a lack of skilled people who can develop and implement AI applications [28]. The cost of developing and implementing AI models is another issue that can be a major obstacle for small- and medium-sized firms, given the need for investment in software, hardware, and human resources [16]. Moreover, organizational change management is necessary to address how authority, roles, and rewards of decision-making should be transformed in the presence of AI [27].

3.4.3 Ethical and regulatory challenges

Another group of AI-related risks is associated with ethical and legal issues. AI applications employed in decision-making in the context of ERP can have the nature of the “black box,” that is, they can make decisions without explaining them, which affects the transparency and accountability [13]. In the context of recruitment or credit scoring, the "black box" algorithms may not be impartial and may perpetuate discrimination [14]. Using AI algorithms to process personal data of customers or employees generates risks related to data privacy and requires companies to fulfill requirements of such regulations as the General Data Protection Regulation [25] and the EU Artificial Intelligence Act [6]. All the surveyed literature on governance emphasizes that companies should ensure that AI models are fair, transparent, and auditable and should be supported with standards and frameworks provided by standardization bodies and regulatory institutions [30,31].

3.5 Comparative Case Analysis of AI–ERP Implementations

This section presents four cases of AI-ERP implementations that were analyzed to contextualize the results of the thematic analysis:

i. Walmart (case: inventory optimization);
ii. Siemens (case: financial and operational forecasting);
iii. General Electric (case: predictive maintenance);
iv. IBM (case: human resource management).

The selection of these cases was based on the following criteria: (1) they belong to different industries and represent different functional domains of ERP systems, and (2) they are the most frequently cited cases in the literature on AI-ERP. The purpose of using these cases in this article is purely illustrative. Practitioner and corporate literature were used only to describe the reported results of AI-ERP deployments.

3.5.1 Walmart: Machine learning for inventory optimization

Walmart is one of the companies most frequently reported to use analytics for optimizing inventory planning. In the context of ERP, the benefit of using ML algorithms for demand forecasting and inventory replenishment planning is not only about improving the accuracy of the forecast but also about speeding up reactions to changes in supply and demand. Results of ML algorithms that predict the demand and generate recommendations on the replenishment can be used for planning procurement and distribution [23,33]. The challenges that can occur in this context are related to aligning outputs of ML algorithms with parameters of ERP planning applications, defining governance for overwriting the outputs of the algorithms, and ensuring that recommendations generated by the algorithms do not violate business constraints such as lead times, supplier reliability, and target service levels.

3.5.2 Siemens: AI-enabled financial and operational forecasting

As an example of cross-functional integration of AI applications with ERP in industry, Siemens is often cited in the literature as a company that connects advanced analytics with operational planning and asset management. The technological challenge in integrating AI with ERP in industry is usually presented as the integration of operational technology (OT) data with master data of ERP to enable the conversion of predictions (e.g., risk of failure) into executable work orders and procurements, which requires well-functioning data flows, standardized hierarchies for structuring master data, and well-defined responsibilities for data quality between the engineering and the IT department [3]. Challenges in the deployment of AI-ERP systems in industry that are reported in the literature are related to ensuring cybersecurity of connected devices, validating algorithms in environments critical for safety, and training of employees to use outputs of algorithms instead of empirical rules [21,34]. This case is used here to summarize reported experiences and challenges with AI-ERP deployments rather than a single case study.

3.5.3 General Electric: Predictive maintenance

General Electric uses an ERP-integrated predictive maintenance system to predict failures of equipment by processing sensor data in real time. Being able to predict failures enables scheduling a maintenance intervention proactively and prevents unplanned downtimes and reduces maintenance costs [35,36]. The example of General Electric shows that the key enablers for AI-enhanced ERP are well-functioning data flows between sensor systems and ERP, as well as organizational capabilities to shift from a reactive to a predictive maintenance culture.

3.5.4 IBM: AI in human resource management

The third case is IBM, which has implemented AI technology in its ERP system to facilitate human capital management. AI technology forecasts employee turnover, identifies the lack of skills, and suggests training programs based on performance records, job satisfaction, and career path [29,37]. As a result, IBM can proactively secure talented employees and distribute human resources efficiently. IBM's case shows the positive effect of AI-supported HR decisions as well as the ethical issue of AI-powered employee evaluation, which necessitates transparency and equity [14,31].

3.6 Comparative Analysis of Leading AI-Enabled ERP Vendors

To further enrich the analysis, three popular ERP solutions, including SAP S/4HANA, Oracle Cloud ERP, and Microsoft Dynamics 365, are compared to figure out how AI-enabled decision support differs from one to another. The three ERP solutions are chosen as they are the most widely adopted solutions, and the way AI technology is embedded into each solution is distinct from the others. This comparison is descriptive and illustrative rather than an in-depth comparison, as it is based on secondary data. Table 2 compares the three solutions in terms of AI-enabled decision support, which shows that differences among them are not about whether AI technology is used or not, but how AI technology is embedded into the decision-making process. Specifically, AI technology in SAP S/4HANA is mainly used for the MRP and manufacturing execution [16]. In Oracle Cloud ERP, AI technology is mainly used for finance and operations management, such as forecasting and control. In Microsoft Dynamics 365, AI technology is used for analytics and can be extended to other Microsoft applications [21].

Table 2
Comparative view of AI capabilities across leading ERP vendors

Criterion	SAP S/4HANA	Oracle Cloud ERP	Microsoft Dynamics 365
AI entry points	Embedded ML/AI for process automation and anomaly detection; SAP analytics ecosystem.	Cloud-native AI/ML features for finance and operations; predictive insights across modules.	AI via Microsoft cloud stack; Power Platform for workflows and analytics.
Supply chain support	Manufacturing-centric, MRP-oriented planning with integrated supply-chain visibility.	Cloud SCM planning and inventory control are linked to finance and procurement.	Forecasting via Azure and Power BI; partner customization for complex manufacturing.
Finance/planning	Real-time postings with embedded analytics, variance detection, and compliance monitoring.	Integrated financial planning, close, and reporting with automated controls.	Extensible FP&A analytics via Power BI; workflow automation via Power Platform.
Typical fit	Large/complex operations needing end-to-end planning and control.	Cloud standardization with strong finance governance priorities.	Rapid workflow automation within the Microsoft ecosystem.

Based on the TOE framework [19], the differences among the three solutions indicate how technological attributes (i. e., solution architecture, embedded AI technology, and integration) affect organizational and environmental attributes in which AI-equipped ERP can be adopted, scaled up, and governed. For example, if an enterprise puts more emphasis on the manufacturing process, it should choose SAP S/4HANA. If an enterprise values cloud-based finance analytics, it should choose Oracle Cloud ERP. If an enterprise has many applications in the Microsoft ecosystem, it should choose Microsoft Dynamics 365. This, in turn, affects the complexity of adoption, as the three solutions require different levels of investment and expertise. For example, as SAP S/4HANA requires a high level of integration with the manufacturing process, a high level of process standardization and data quality should be achieved before AI technology can be adopted. Oracle Cloud ERP and Microsoft Dynamics 365 have no requirement for a huge investment in IT infrastructure, but they also bring the potential risk of IT governance fragmentation [4,11]. Therefore, enterprises should not only consider whether AI-equipped decision support is provided, but also consider what level of investment and expertise should be made, and what level of risk should be taken.

3.7 Cross-Case Synthesis

Based on the within-case analysis, several observations have been made across the cases (Table 3). First, the cases suggest that AI-equipped decision support brings improvement in forecasting, equipment maintenance, inventory management, and human capital management [9,12]. Second, AI-powered prediction enables enterprises to make proactive decisions to respond to potential risks, such as supply chain risk, equipment failure risk, and financial risk [9,10]. Third, automation of routine decisions, such as inventory replenishment, production scheduling and applicant screening, saves time and resources for strategic decisions, but clear rules and regulations should be developed for exception management [8,38]. Fourth, successful adoption of AI-equipped decision support requires changes in employees' skills, roles, and trust [27,28]. Cumulatively, these results demonstrate the interlinked validity of the TOE framework [19]: technology (AI model maturity and ERP integration scope), organization (data management, expertise, and change capacity), and environment (compliance requirements and market conditions) together explain whether investments in AI-ERP deliver durable improvements in decision quality. In Table 3, module abbreviations follow SAP S/4HANA naming conventions as the most widely deployed enterprise ERP architecture.

Table 3
Cross-domain synthesis: AI technique, ERP function, decision-support contribution, and implementation risk

AI technique	ERP function/module	Decision-support contribution	Key implementation risk
Machine learning (demand forecasting)	MM/SD (inventory & supply chain)	Reduces stockouts and overstocking; dynamic replenishment via pattern recognition on sales orders and supplier lead times.	Model drift as demand patterns shift; requires clean, governed master data across MM and SD modules.
Predictive analytics (financial)	FI/CO (financial planning & control)	Proactive budgeting, variance detection, working capital optimization, and early fraud flagging in GL and AP/AR transactions.	Over-reliance on predictions during structural shocks; explainability requirements in regulated finance contexts.
Natural language processing	CRM/HCM (customer & HR decisions)	Sentiment-aware demand sensing from unstructured channels; accelerated HR screening and employee query resolution.	Noisy or biased training data; General Data Protection Regulation compliance for processing personal communications and HR records.
Anomaly detection / ML (finance)	FI (fraud & risk management)	Real-time flagging of unusual transaction behavior in AP and GL; strengthens internal controls.	High false-positive rates require human review capacity; bias risk in automated transaction scoring.
Explainable AI	Cross-functional (governance layer)	Increases trust and adoption by surfacing decision rationale; supports auditability in regulated domains.	Added model complexity; governance overhead for maintaining explanation artifacts alongside model versions.
Predictive maintenance (IoT + ML)	PM / PP (asset & production management)	Reduces unplanned downtime by forecasting equipment failure from sensor data integrated into ERP work orders.	Requires robust OT-IT data pipelines; organizational transition from reactive to predictive maintenance culture.

MM = Materials Management; SD = Sales and Distribution; FI = Financial Accounting; CO = Controlling; CRM = Customer Relationship Management; HCM = Human Capital Management; PM = Plant Maintenance; PP = Production Planning.

4. Conclusion

This systematic review and comparative case study show that AI-powered ERP is linked to significant gains in decision quality at the organizational level, including better forecast accuracy, faster problem identification, and flexible process alignment, albeit with considerable variation in the degree of benefit, depending on contextual factors. The most valuable returns are realized when AI is deeply coupled with master data in the ERP system, subject to high-quality data management, and tied to decision-making with clear responsibility for results. The two conceptual models, socio-technical systems theory and the resource-based view, validate the notion that the value of AI in ERP systems is not simply a technological issue but requires the coordinated development of data, algorithms, management systems, and organizational practices.

While substantial benefits are identified, the evidence also points to a number of repeated risks in the adoption of AI-enhanced ERP. Poorly standardized data between modules compromises the predictive value of AI. Poor interpretability of AI results leads to confidence issues that can limit uptake. Resistance from end users can occur if AI suggestions undermine established norms, especially when training and change support are inadequate. Therefore, the effectiveness of AI for decision-making within the ERP should be assessed not just in terms of predictive performance but also in terms of the rate of operational use and the actual impact on business process KPIs.

4.1 Practical Recommendations

A staged approach is suggested for practitioners. First, data management and standards for master data in the ERP system should be defined as a prerequisite for deploying AI. Second, AI models should be implemented with clear performance standards and plans for maintaining those standards, including model drift detection and retraining. AI results should be incorporated into the ERP application with clear rules for human override and traceability to ensure that decision makers remain responsible for key choices. Training should be provided to clarify when AI advice should be heeded and when it is automated, an aspect critical to supporting trust and regular usage. Implementation should also include plans for operationalization that incorporate ML operations, such as versioning, security for data flows, and compliance in regulated contexts.

4.2 Future Research Directions

Future research should focus on comparative analysis of the business value of AI in ERP applications across sectors, using common metrics like forecast accuracy improvement, cycle time reduction, and override rate. Longitudinal research on organizational learning and data management maturity is needed to clarify the trajectory of value creation from AI in ERP. Further research is needed on questions of ethical and legal liability for automated advice, on the utility of process mining for diagnosing decision-making bottlenecks in AI-enabled ERP processes, and on scalable architecture patterns for integrating transactional ERP systems with data lake or lakehouse architectures for handling semi- and unstructured data and for real-time analytics. The evolving regulatory environment, including the EU AI Act and related international efforts, offers both motivation and a framework for research into the governance of responsible AI in the enterprise.

4.3 Final Remarks

AI in ERP is best understood as a socio-technical capability whose performance depends on the interplay of data quality, model governance, organizational readiness, and human decision-making practices. A research and implementation focus on measurable outcomes, transparent governance, and robust data architectures will be decisive in translating AI potential into durable enterprise value.

Conflict of Interest
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