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AI-DRIVEN ENTERPRISE SYSTEMS: A FRAMEWORK FOR DIGITAL TRANSFORMATION, INTELLIGENT INTEGRATION, AND FUTURE BUSINESS OPERATIONS

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ABSTRACT

Objective: This study aims to develop a comprehensive conceptual framework for Artificial Intelligence-Driven Enterprise Systems (AI-ES) by synthesizing recent literature on the integration of Artificial Intelligence (AI) within Enterprise Systems and examining its role in enabling intelligent business operations and digital transformation.

Research Design & Methods: A Systematic Literature Review (SLR) was conducted following a structured review protocol. The selected studies were analyzed using thematic synthesis and classified into four interconnected analytical layers: AI Technology Layer, Intelligent Enterprise System Layer, Business Intelligence Layer, and Business Outcome Layer.

Findings: The review indicates that AI technologies including Machine Learning, Deep Learning, Natural Language Processing, Large Language Models, Predictive Analytics, IoT, and cloud computing serve as the technological foundation for intelligent enterprise systems. Their integration into ERP, CRM, PLM, and enterprise platforms enhances intelligent process automation, predictive decision support, supply chain optimization, and real-time data integration. These capabilities collectively strengthen business intelligence by improving analytics, forecasting, operational visibility, and adaptive decision-making, ultimately leading to operational excellence, organizational agility, innovation capability, competitive advantage, and sustainable business performance.

Implications: The proposed framework provides practical guidance for organizations seeking to implement AI-enabled Enterprise Systems by emphasizing the importance of technological readiness, enterprise integration, data governance, interoperability, and organizational capabilities as prerequisites for successful digital transformation.

Contribution & Value Added: This study contributes by proposing a holistic AI-Driven Enterprise Systems Framework that integrates AI technologies, intelligent enterprise platforms, business intelligence capabilities, and business outcomes into a unified conceptual model. The framework extends existing Enterprise Systems literature by offering a structured foundation for future empirical research and practical AI adoption strategies in digital enterprises.

Keywords: Artificial Intelligence, Enterprise Systems, Digital Transformation, Business Intelligence.

JEL codes: M15, O33
Article type: Review paper

INTRODUCTION

The increasingly complex global business environment has prompted organizations to adopt Enterprise Systems (ES) as a strategic infrastructure for integrating business processes, information, technology, and organizational resources. Enterprise Systems not only serve as operational support systems, but also function as integrated systems capable of connecting various organizational activities through the integration of data, applications, and business processes. The complexity of enterprise systems stems from the fact that these systems involve multidimensional interactions; as a result, they are often implemented to solve complex problems in various industrial sectors, such as energy, finance, manufacturing, and defense (Huiping, 2009; Wilamowski, 2005). In this context, enterprise systems play a crucial role in supporting operational efficiency, coordination among organizational units, and enhancing the company's ability to adapt to a dynamic business environment.

Enterprise Systems have evolved from standardized systems to systems that are more adaptable to the specific needs of organizations. Each organization has distinct business processes, organizational structures, technology infrastructures, and information needs; therefore, the implementation of ES often requires various forms of customization, such as system configuration, the use of add-ons, and other adaptation mechanisms to meet specific operational needs (Galster and Avgeriou, 2015). This variability indicates that the successful implementation of enterprise systems depends not only on technological capabilities, but also on the alignment between the system, organizational strategy, and the context of its implementation.

The paradigm shift in Enterprise Systems development is also influenced by advances in digital technology, especially cloud computing, which has changed the way organizations design, implement, and manage enterprise systems. Cloud technology enables increased flexibility, scalability, automation, and cost efficiency by providing digital infrastructure and services that are easier to develop than traditional systems (Chen et al., 2014; Yu and Osathanunkul, 2023). The cloud-based approach also supports faster information integration, cross-organizational collaboration, and the management of large amounts of data to support modern business analytics needs.

In addition to technological aspects, the development of Enterprise Systems is also heavily influenced by social, cultural, and organizational readiness factors. Non-technical factors such as organizational change management, management support, work culture, and concerns about organizational change control can be barriers to successful enterprise system implementation (Bala et al., 2021). In developing countries, limited technological infrastructure, low human resource readiness, and lack of training are the main challenges in implementing Enterprise Systems, especially cloud-based ERP systems (Yu and Osathanunkul, 2023). Therefore, a systems-based approach and Enterprise Architecture (EA) are becoming increasingly important to understand the relationship between business processes, technology, information, and organizational structure in designing effective enterprise systems (Gorkhali and Xu, 2019; Pańkowska, 2017). Recent developments show that Enterprise Systems are continuing to move towards a smarter digital ecosystem through the integration of technologies such as the Internet of Things (IoT), Software-as-a-Service (SaaS), cloud computing, and Artificial Intelligence (AI) to improve the efficiency, flexibility, and decision-making capabilities of organizations (Chen et al., 2014; Sun, 2021). This technology integration shows a paradigm shift from traditional Enterprise Systems that are oriented towards transaction integration to systems that are able to provide data analysis, process automation, and decision support in a more adaptive manner.

The development of AI is transforming enterprise systems into more intelligent, adaptive, and data-driven systems. The integration of AI into enterprise systems enables organizations to improve operational efficiency through faster and more accurate business process automation, document processing, data analysis, and optimization of organizational activities (Balakayeva et al., 2025; Dziembek and Turek, 2025; Thambireddy et al., 2025). In contrast to traditional enterprise systems that are more oriented towards transaction processing, AI-based Enterprise Systems are able to utilize historical and real-time data to produce predictive analytics that support strategic decision-making and reduce reliance on manual processes (Abuowaida et al., 2025; Hundekari et al., 2025).

In addition to improving internal efficiency, AI also expands Enterprise Systems' capabilities in addressing market dynamics through predicting business trends, understanding customer behavior, and providing more personalized services. These capabilities make AI a critical component in building organizations that are more responsive to changes in the business environment, particularly in the manufacturing, retail, financial, and supply chain sectors (Aliverdiyev, 2025; Munir and Kristian, 2025; Parveen Roja et al., 2024). In its implementation, the integration of AI into Enterprise Systems is supported by various technologies such as machine learning, natural language processing (NLP), and generative AI, which strengthen the system's capabilities in performing analysis, communication, and context-based decision automation (Balakayeva et al., 2025; Thambireddy et al., 2025; Wang et al., 2025).

Furthermore, the development of AI-based Enterprise Systems does not stand alone, but develops through combination with other digital technologies such as the Internet of Things (IoT), blockchain, and edge computing which form a more connected and adaptive digital ecosystem (Evangeline, 2025; Macha, 2025). The integration of these various technologies indicates a shift towards the concept of Intelligent Enterprise Systems (IES), namely enterprise systems that not only manage information but also have the ability to learn, adapt, and support intelligent decision-making as part of an organization's digital transformation.

While the integration of Artificial Intelligence (AI) offers significant opportunities to enhance the capabilities of Enterprise Systems, implementing AI in an organizational environment still faces various technical, strategic, and organizational challenges. One of the main obstacles is the low organizational readiness to adopt AI technology, particularly regarding the availability of quality data, technological infrastructure, and the competence of human resources capable of managing and optimally utilizing this technology (Hussein et al., 2026). In addition, the misalignment between AI adoption strategies and organizational business objectives can hinder the achievement of maximum technology benefits because many organizations do not yet have AI performance measurement mechanisms that are integrated with business strategies (Sira, 2025).

In addition to organizational readiness, human and cultural aspects also pose significant challenges in AI-based Enterprise Systems transformation. Resistance to change, concerns about the impact of automation, and low user acceptance of AI-based systems can slow the implementation of new technologies (Harmon et al., 2025; Hussein et al., 2026). From a technical perspective, integrating AI into existing enterprise systems often faces complexities due to differences in system architecture, uncertain technology requirements, resource constraints, and the need to adapt to existing infrastructure (Clemens et al., 2023; Kim et al., 2023). Other issues such as data quality, information security, privacy, and implementation costs are also inhibiting factors, especially for organizations with limited resources such as small and medium enterprises (SMEs) (Clemens et al., 2023).

Based on these challenges, there remains a research gap in understanding how AI can be effectively integrated into Enterprise Systems architecture to support an organization's digital transformation. Most previous research has focused on the technical aspects of AI or the implementation of specific technologies in isolation, while studies linking strategic, technological, and human perspectives in building AI-based enterprise systems are still limited. Furthermore, research on an AI implementation framework capable of bridging the gap between organizational needs, technology readiness, and the digital transformation process still requires further development.

This gap is increasingly visible in the context of certain industries and regions, especially the manufacturing sector, SMEs, and organizations in developing countries that have different infrastructure characteristics, resources, and levels of digital readiness. Therefore, research is needed to explain how AI integration in Enterprise Systems can be designed contextually, taking into account technological, organizational, and environmental aspects of implementation. Furthermore, a multidisciplinary approach that combines perspectives from information systems, AI technology, data governance, ethics, and change management is essential to producing a sustainable AI implementation model.

Based on this research gap, this study aims to develop an Artificial Intelligence-Driven Enterprise Systems framework as a conceptual approach to integrating AI capabilities into modern enterprise systems. This framework focuses on how AI can enhance four key Enterprise Systems capabilities: business process automation, predictive decision-making, supply chain optimization, and real-time data integration. This research is expected to provide theoretical contributions to the development of the Intelligent Enterprise Systems (IES) concept and provide practical implications for organizations in designing AI-based digital transformation strategies.

LITERATURE REVIEW

Enterprise Systems (ES)

Enterprise Systems (ES) are large-scale integrated information systems designed to coordinate business processes, align information flows, and manage an organization's resources comprehensively. The development of ES is a response to the increasing complexity of organizational coordination and the need for companies to have systems capable of effectively integrating various business functions (Maruf, 2025; Mhaskey, 2024). The evolution of Enterprise Systems demonstrates a paradigm shift from transaction-based systems to intelligent systems through several stages of development, namely Enterprise Resource Planning (ERP), ERP II, ERP III, and Intelligent Enterprise Systems (IES). ERP focuses on internal organizational integration through the use of a centralized database that replaces separate information systems, thereby reducing data redundancy and increasing the standardization of business processes such as finance, manufacturing, and human resources (Mhaskey, 2024). Furthermore, ERP II expands the scope of integration by connecting the organization's internal processes with customers and business partners through modules such as Supplier Relationship Management (SRM), Product Lifecycle Management (PLM), as well as Service-Oriented Architecture (SOA) technology support to improve system interoperability (Vasilev, 2014). The next development, ERP III expands the capabilities of enterprise systems through the integration of cloud computing, social technology, unstructured data analysis, and knowledge management to support collaboration and utilization of organizational knowledge. The latest stage of development is Intelligent Enterprise Systems (IES), which integrates technologies such as in-memory computing and Artificial Intelligence (AI) into the core processes of an organization, so that the system is able to carry out self-learning, adapt to changes in the business environment, and support more autonomous decision-making (Sajja et al., 2025).

Artificial Intelligence in Enterprise Systems

The integration of Artificial Intelligence (AI) into enterprise systems marks a paradigm shift from static, rule-based systems to adaptive systems capable of learning from data and making decisions based on intelligent analytics (Mhaskey, 2024). AI plays a role in restructuring the architecture of enterprise systems by enhancing automation capabilities, predictive analytics, business process optimization, and real-time information integration. One of the key applications is Intelligent Business Process Automation, in which AI is combined with technologies such as Robotic Process Automation (RPA) and Natural Language Processing (NLP) to improve the efficiency of business processes. Unlike traditional automation, which is static, AI-based automation can understand unstructured data, automatically extract information, adapt workflows, and reduce reliance on manual tasks. In addition, AI enhances Predictive Decision Support capabilities by transforming the decision-making process from a reactive approach based on historical reports to a proactive approach through demand forecasting, risk analysis, financial forecasting, and data-driven decision recommendations (Martin and Nair, 2024). The implementation of intelligence models such as Bayesian Networks and Graph Neural Networks (GNN) enables enterprise systems to detect anomalous patterns, improve decision-making accuracy, and support faster large-scale data processing (Pakkirisamy, 2025).

In the context of supply chains, AI has become a key component in the development of AI-Based Supply Chain Optimization because it enhances the ability of enterprise systems to cope with the uncertainty and complexity of the global business environment (Beth et al., 2026). Through the application of machine learning and predictive analytics, AI can be used to forecast inventory needs, optimize distribution, manage supplier risk, and improve supply chain operational efficiency in real time. In addition, the integration of AI with Internet of Things (IoT) technology and cloud computing enhances real-time data integration capabilities by enabling enterprise systems to collect, process, and analyze operational data directly from various sources, such as sensors and RFID devices (Bonthu, 2025; Sahara and Aamer, 2022). Data quality management mechanisms such as Data Quality as a Service (DaaS) also enable the automatic validation, cleansing, and synchronization of data, thereby improving the accuracy of an organization's information. Thus, the integration of AI transforms Enterprise Systems into Intelligent Enterprise Systems (IES), which not only function as information integration systems but also as intelligent platforms capable of learning, adapting, and supporting an organization's strategic decision-making.

Table 1. The Role of Artificial Intelligence in Enterprise Systems

The Role of AI in Enterprise Systems	**Key Concepts**	**Supporting Technologies**	**The Role of AI in Enterprise Systems**	**Impact/Benefits**
Intelligent Business Process Automation	Transformation of business processes from rule-based automation to adaptive, intelligent automation.	Artificial Intelligence (AI), Robotic Process Automation (RPA), Natural Language Processing (NLP)	Automate routine tasks, process unstructured data, extract information from documents, and dynamically optimize workflows.	Improve process efficiency, reduce manual tasks, speed up the completion of administrative work, and reduce human intervention by up to 65%.
Predictive Decision Support	Shift in decision-making from a reactive approach based on historical reports to data-driven, predictive decisions.	Machine Learning, Bayesian Network, Graph Neural Networks (GNN), Predictive Analytics	Performing demand forecasting, risk analysis, financial forecasting, anomaly detection, and providing intelligent business decision recommendations.	Improving decision-making accuracy, accelerating business analysis, supporting fraud detection, and enabling real-time strategic decision-making.
AI-Based Supply Chain Optimization	Development of a supply chain system that is adaptive to changes and disruptions in the business environment.	Machine Learning, Advanced Analytics, AI Forecasting	Optimizing inventory, predicting stock requirements, managing supplier risk, and improving distribution coordination in real time.	Reducing the risk of stockouts by up to 27%, lowering storage costs by up to 18%, and improving supply chain operational cost efficiency.
Real-Time Data Integration	Rapid and accurate integration of data from various operational sources to support an intelligent enterprise system.	AI, Internet of Things (IoT), Cloud Computing, RFID, Data Quality as a Service	Automatically acquiring, validating, cleaning, and analyzing sensor data to generate real-time insights.	Improving data quality, maintaining information consistency across systems, and supporting more accurate operational monitoring.

Digital Transformation Theory

The theory of digital transformation explains that the adoption of digital technology is not merely the implementation of new tools to improve operational activities, but rather a process of sociotechnical change that involves the transformation of business models, organizational processes, and customer experiences, as well as the creation of sustainable business value (Ilham et al., 2026). In the context of this study, AI-Driven Enterprise Systems are viewed as a key enabler of digital transformation because they can enhance organizational capabilities by integrating artificial intelligence into business processes and decision-making. The implementation of AI-based systems supports the achievement of operational excellence through process automation, resource optimization, and the reduction of human error, thereby increasing the organization's productivity and operational efficiency (Mhaskey, 2024). In addition, AI also enhances business agility by improving an organization's ability to detect changes in the business environment (sensing) and respond more quickly to opportunities and threats (responding).

Furthermore, AI-driven digital transformation contributes to enhancing innovation capabilities by accelerating product development, increasing service flexibility, and leveraging data analytics to create new business solutions (Rizana et al., 2025). The integration of cloud and AI enables organizations to accelerate their innovation cycles and improve their ability to respond to customer needs (Shaik, 2024). In terms of sustainable performance, the implementation of AI in enterprise systems supports organizational sustainability by enhancing monitoring automation, reducing operational risks, improving compliance, and optimizing the organization's financial performance (Pohrib et al., 2025). Thus, the theory of digital transformation serves as the conceptual foundation for the idea that AI-Driven Enterprise Systems function not merely as supporting technologies, but as a transformation strategy that enables organizations to achieve competitive advantage through efficiency, adaptability, innovation, and sustainability.

METHODS

This study employs a Systematic Literature Review (SLR) approach to systematically identify, evaluate, and synthesize the findings of previous research on the integration of Artificial Intelligence (AI) into the development of Enterprise Systems toward Intelligent Enterprise Systems (IES). The SLR approach was chosen because it provides a systematic, transparent, objective, and replicable review process, thereby minimizing potential bias in the literature synthesis process (Jansen, 2017). In addition to producing a knowledge synthesis, this study also applies a conceptual framework development approach to develop a conceptual model that explains the relationship between AI capabilities, Intelligent Enterprise Systems capabilities, and organizational digital transformation performance. The research data sources were obtained through a literature search in four reputable scientific databases, namely Scopus, IEEE Xplore, ScienceDirect, and SpringerLink, which were selected because they have a coverage of quality publications in the fields of information systems, artificial intelligence, enterprise architecture, and digital transformation (Syed, 2025).

The search strategy used a combination of keywords with Boolean operators, namely ("Artificial Intelligence" OR "AI") AND ("Enterprise Systems" OR "ERP") AND ("Intelligent Enterprise Systems") AND ("Digital Transformation") AND ("AI-based Business Process Automation"). The literature selection process followed the guidelines of Tranfield et al. (2003), which included three main stages: literature identification, literature classification, and framework development. The literature identification stage was carried out by filtering articles based on title and abstract, and eliminating duplicate documents. Focusing on reputable international journal articles published within the last ten years to maintain the relevance of technological developments. Furthermore, in the literature classification stage, the selected articles were grouped into five main themes: AI integration in Enterprise Systems architecture, intelligent business process automation, predictive analytics, AI-based supply chain intelligence, and IoT-based real-time data integration. The final stage, namely framework development, is carried out through an inductive analysis of the results of literature synthesis to build a conceptual framework that explains the relationship between Artificial Intelligence Capability as a driving variable, Intelligent Enterprise Systems Capability as a core capability realized through business process automation, predictive decision making, supply chain optimization, and real-time data integration, and Digital Transformation Performance as the main output of the organization.

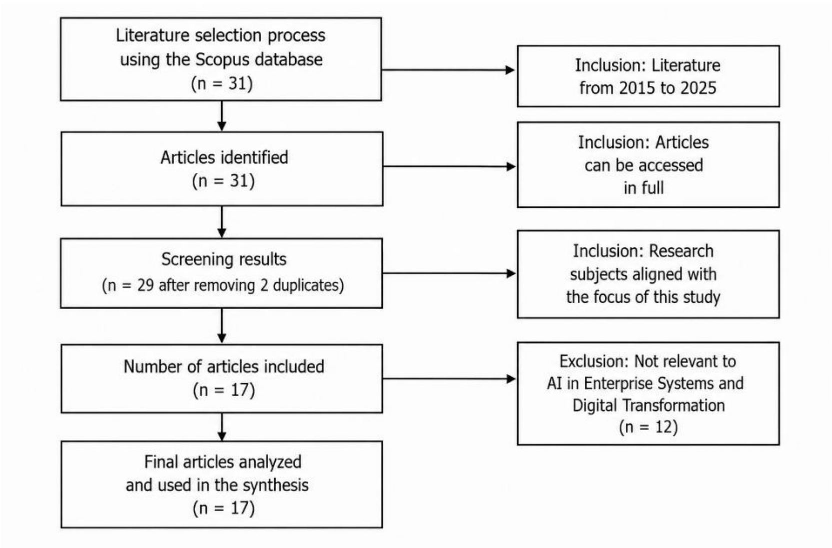

Figure 1. PRISMA Flow Diagram of the Literature Selection Process

RESULT

As the main contribution of this research, a comprehensive conceptual framework named the AI-ES Framework (Artificial Intelligence-Driven Enterprise Systems Framework) was developed. Unlike traditional architectural approaches that treat analytics engines as separate external modules (silos), the AI-ES Framework embeds cognitive intelligence directly into the core architecture of information systems. This framework is organized into a four-layer structure in which the layers are hierarchically interdependent.

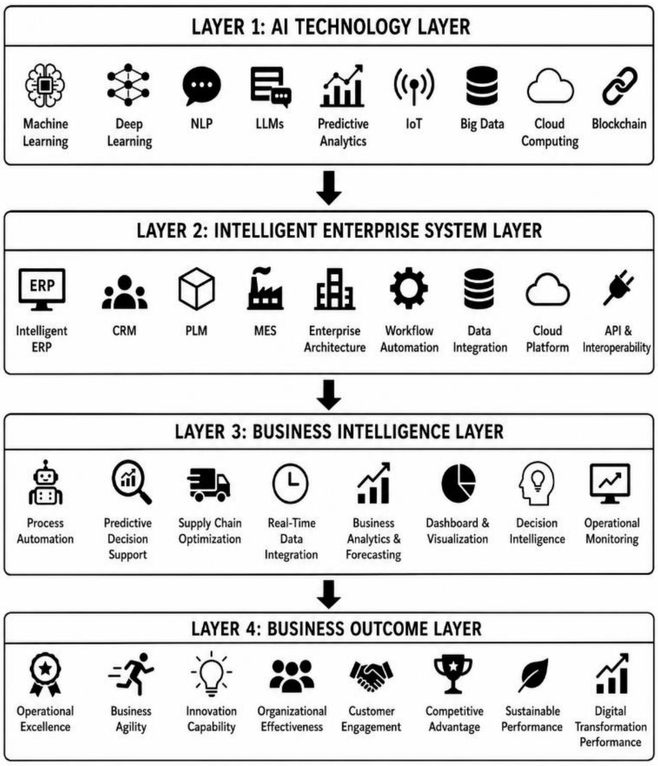

Figure 2. Conceptual Framework of AI-Driven Enterprise Systems

AI Technology Layer

The first layer is the cognitive technology foundation that serves as the provider of intelligent computing capacity for the entire system. The key technological components in this layer include:

1. Artificial Intelligence (AI) and Machine Learning (ML)

Artificial Intelligence (AI) and Machine Learning (ML) are the core technologies most frequently identified in the literature as the foundation for developing Intelligent Enterprise Systems. Various learning algorithms, such as supervised learning, unsupervised learning, ensemble learning, and reinforcement learning, enable systems to learn historical patterns, perform classification, customer segmentation, anomaly detection, and generate increasingly accurate predictions as data grows. In addition, ML is also used to optimize logistics processes, inventory management, customer behavior analysis, and support adaptive decision making in dynamic enterprise environments (Iazza et al., 2026; Leite et al., 2026; Rahman et al., 2026; Rainy et al., 2023).

2. Deep Learning (DL)

Deep Learning is a further development of Machine Learning that uses deep neural networks to recognize complex data patterns. Literature shows that this technology is widely used for time-series forecasting, anomaly detection, image analysis, high-dimensional data classification, and even natural language understanding. Deep Learning's ability to automatically extract features makes it an essential technology for modern enterprise systems that require large-scale data analysis (Leite et al., 2026; Rainy et al., 2023).

3. Natural Language Processing (NLP) and Large Language Models (LLMs)

Natural Language Processing (NLP) is a key component that enables Enterprise Systems to understand and process unstructured data, such as business documents, emails, technical reports, customer reviews, and operational activity records. Recent developments show that NLP is increasingly being strengthened through the use of Large Language Models (LLMs), which are capable of reasoning, information extraction, document classification, and even automated report generation through prompt engineering and Retrieval-Augmented Generation (RAG) techniques. Integrating LLMs with a company's knowledge base enables the system to provide more contextual recommendations while minimizing misinformation (hallucinations) (Lin and Dang, 2026; Rainy et al., 2023; Villafuerte et al., 2026).

4. Predictive Analytics and Intelligent Decision Support

The next component is Predictive Analytics, which transforms historical and real-time data into predictions of an organization's future conditions. This technology supports various enterprise functions, such as market demand prediction, fraud detection, risk management, energy optimization, cybersecurity, and business scenario simulation. The integration of AI into Decision Support Systems (DSS) results in a decision support system capable of providing adaptive recommendations based on continuous changes in the business environment (Hidayatullah et al., 2026; Rahman et al., 2026; Rainy et al., 2023).

5. Intelligent Data Management and Data Integration

The findings of the synthesis also indicate that the success of AI implementation is heavily influenced by the system's ability to intelligently manage enterprise data. These components include Intelligent Data Ingestion, Semantic Harmonization, Master Data Synchronization, and mechanisms for data interoperability across enterprise applications. An approach based on ontologies, embeddings, and AI enables the system to integrate data from ERP, CRM, IoT, and external sources, resulting in higher data quality and supporting cross-functional decision-making within the organization (Rahman et al., 2026; Xu, 2011).

6. Business Process Intelligence and Workflow Automation

In addition to data analytics, the AI Technology Layer is also supported by technologies focused on business process optimization. The literature identifies Business Process Management (BPM), Workflow Management Systems (WfMS), Enterprise Application Integration (EAI), and Service-Oriented Architecture (SOA) as components that enable workflow automation, enterprise application integration, and business process standardization. These technologies serve as a bridge between AI capabilities and their practical implementation in an organization's operational activities (Xu, 2011).

7. Internet of Things (IoT), Big Data, and Cloud-Based Infrastructure

Most studies identify the Internet of Things (IoT), big data analytics, and digital infrastructure as the key supporting components of the AI technology layer. IoT sensors generate operational data in real time, while big data analytics enables the processing of large volumes of data to support forecasting, logistics optimization, and predictive maintenance. Modern computing infrastructure also enables continuous data synchronization, allowing the entire enterprise system to operate in an integrated manner and respond to changing business conditions (Iazza et al., 2026; Leite et al., 2026; Xu, 2011).

8. Intelligent Security, Governance, and Blockchain

Some literature expands the AI Technology Layer to include mechanisms such as Adaptive Governance, Explainable AI, Compliance Monitoring, and Blockchain Technology. These components aim to ensure data security, transparency in decision-making processes, accountability in the use of AI, and the integrity of data exchange between organizations. Thus, AI not only enhances system intelligence but also strengthens the governance and sustainability aspects of Enterprise Systems implementation (Iazza et al., 2026).

Intelligent Enterprise System Layer

1. Intelligent Enterprise Resource Planning (Intelligent ERP)

The key component of this layer is Intelligent Enterprise Resource Planning (ERP), which represents the evolution of traditional ERP into an enterprise platform powered by artificial intelligence. Various studies show that ERP no longer functions merely as a transactional system but has evolved into an intelligent platform capable of demand forecasting, inventory optimization, supply chain analysis, business process automation, and supporting data-driven decision-making. Several studies have even introduced the concept of Agentic ERP, an ERP system capable of autonomously executing transactions based on intent-oriented execution through AI agents. This development marks the transformation of ERP into a key foundation for Intelligent Enterprise Systems (Chu, 2026; Fei et al., 2025; Hidayatullah et al., 2026; Lawendatu et al., 2026; Trunina et al., 2026).

2. Enterprise Business Platforms (CRM, SCM, EMS, PLM, MES)

In addition to ERP, literature shows that Intelligent Enterprise Systems are also built through the integration of various business platforms such as Customer Relationship Management (CRM), Supply Chain Management (SCM), Enterprise Management System (EMS), Product Lifecycle Management (PLM), and Manufacturing Execution System (MES). This integration enables organizations to connect marketing, production, logistics, customer service, and energy management activities into a single, unified digital ecosystem. AI is then leveraged to enhance personalized customer service, supply chain coordination, product lifecycle management, and real-time manufacturing process optimization (Fei et al., 2025; Iazza et al., 2026; Lin and Dang, 2026; Rainy et al., 2023).

3. Enterprise Architecture and System Integration

The synthesis results show that Enterprise Architecture (EA) serves as the structural foundation for building Intelligent Enterprise Systems. Enterprise Architecture connects business strategy, organizational processes, data, applications, and technology infrastructure into an integrated framework. AI implementation is strengthened through Service-Oriented Architecture (SOA), Application Programming Interfaces (APIs), system interoperability, and integration capabilities between new technologies and legacy systems. These integration capabilities enable organizations to build enterprise platforms that are flexible, scalable, and adaptable to changes in the business environment (AL-Ghamdi, 2026; Xu, 2011).

4. Intelligent Data Management and Enterprise Data Integration

The next component is Intelligent Data Management, which automatically manages the entire lifecycle of an organization's data. Literature shows that AI enables real-time data synchronization, data cleansing, data schema harmonization, duplication elimination, and adaptive master data management. Furthermore, data integration is achieved through APIs, semantic frameworks, and interoperability mechanisms, allowing data from ERP, CRM, IoT, and external systems to be used consistently to support cross-functional decision-making (Lawendatu et al., 2026; Leite et al., 2026; Rahman et al., 2026).

5. Cloud-Based Enterprise Platform

Most research positions cloud computing as the primary infrastructure for intelligent enterprise systems. Cloud platforms enable all enterprise applications, databases, AI services, and business dashboards to be integrated into a flexible and scalable computing environment. Cloud computing also enhances collaboration between organizational units, accelerates data access, and supports the implementation of AI-based enterprise services without the limitations of on-premises infrastructure. Examples of implementations include the use of Microsoft Azure, PostgreSQL, and cloud-based ERP platforms that support centralized data analysis (Ergün, 2026; Iazza et al., 2026; Villafuerte et al., 2026).

6. Workflow Automation and Business Process Integration

Intelligent Enterprise Systems are characterized by their capabilities for Workflow Automation and Business Process Integration. AI is integrated into an organization's workflow, automating administrative processes, data validation, reporting, digital marketing, energy management, and production process coordination. This business process integration improves operational efficiency, reduces manual intervention, and accelerates the flow of information between organizational units (Fei et al., 2025).

7. Enterprise Database, Knowledge Management, and Human-in-the-Loop

The literature identifies that Intelligent Enterprise Systems require a standardized enterprise database as the central repository for organizational data. Data management is supported by schema validation mechanisms, version control, knowledge management, and a Human-in-the-Loop approach, which involves users in verifying AI results before they are used in business processes. This approach improves the accuracy, transparency, and traceability of information, ensuring that decisions remain accountable (Lin and Dang, 2026; Villafuerte et al., 2026; Xu, 2011).

8. Organizational Readiness and Digital Integration Capability

In addition to technological aspects, the success of Intelligent Enterprise Systems is also influenced by the organization's technological readiness and integration capability. Research shows that infrastructure readiness, human resource competency, data governance, and the ability to integrate AI with legacy systems are critical factors in building intelligent Enterprise Systems. Organizations with strong integration capabilities tend to be more successful in implementing AI and achieve increased efficiency, innovation, and business competitiveness (AL-Ghamdi, 2026).

Business Outcome Layer

Based on a synthesis of the analyzed literature, the Business Outcome Layer is the highest layer in the Artificial Intelligence-Driven Enterprise Systems framework, representing the tangible impact of Artificial Intelligence implementation on organizational performance. This layer demonstrates how the integration of AI, Intelligent Enterprise Systems, and Business Intelligence generates business value through increased operational efficiency, decision quality, organizational agility, competitiveness, and the sustainability of digital transformation. The synthesis results indicate that the components in this layer can be grouped into several key outcomes.

1. Operational Excellence dan Operational Efficiency

Research findings indicate that the most dominant outcome of AI implementation is increased Operational Excellence. Integrating AI into Enterprise Systems can improve operational efficiency through business process automation, reduced planning cycle times, increased decision accuracy, procurement optimization, and reduced inventory costs, enabling organizations to respond to operational changes more quickly and accurately (Rainy et al., 2023). In addition, improved data quality, real-time data synchronization, and intelligent decision-making contribute to improving the organization's overall operational performance, including reducing operational costs and accelerating the information analysis process (Rahman et al., 2026). Other research also shows that integrated Enterprise Systems can increase organizational efficiency, strengthen global competitiveness, and improve coordination of business processes across organizations (Xu, 2011). The implementation of cloud-based AI also results in increased operational efficiency through automated reporting, real-time traceability, and optimization of production process quality (Villafuerte et al., 2026). Similar findings were obtained in the manufacturing and logistics sectors, which showed increased productivity, reduced production waste, inventory efficiency, and decreased operational costs due to AI-based process automation (Ergün, 2026; Gonçalves et al., 2022; Iazza et al., 2026; Leite et al., 2026).

2. Strategic Decision Quality and Data-Driven Decision Making

The implementation of AI also improves the quality of strategic decision-making. AI-based enterprise systems generate more accurate, timely recommendations that align with the organization's strategic objectives, strengthening the evidence-based decision-making process (Chu, 2026). AI enables organizations to leverage predictive analytics, scenario simulation, and adaptive learning to improve the accuracy of strategic and operational decisions (Rahman et al., 2026; Rainy et al., 2023). In Distributed ERP implementation, AI generates automated reports and insights that can be directly utilized by management to support strategic and operational decisions (Villafuerte et al., 2026). In addition, integrated Enterprise Architecture improves information consistency so that business decisions become more transparent and strategically valuable (AL-Ghamdi, 2026).

3. Business Agility and Organizational Responsiveness

A literature synthesis shows that AI improves business agility, which is an organization's ability to respond quickly to changes in the business environment. AI enables dynamic resource allocation, real-time decision-making, and adaptation to rapidly changing market conditions, thereby increasing organizational agility in the face of business volatility (Rainy et al., 2023). Organizations also gain the ability to respond more adaptively to regulatory changes, market fluctuations, and customer needs through data synchronization and business process automation (Rahman et al., 2026). In the logistics sector, digital transformation increases supply chain flexibility, distribution visibility, and an organization's ability to respond to global disruptions, thereby strengthening the company's operational resilience (Iazza et al., 2026). Other research findings show that AI-based ERP improves an organization's ability to adapt to market changes while strengthening long-term competitiveness (AL-Ghamdi, 2026; Fei et al., 2025; Lawendatu et al., 2026; Somanathan, 2025; Trunina et al., 2026).

4. Productivity, Cost Reduction, dan Resource Optimization

Most studies show that AI has a direct impact on improving organizational productivity. AI implementation results in reduced operational costs through the automation of administrative activities, optimized inventory management, more efficient use of resources, and an increased return on investment (ROI) (Iazza et al., 2026; Lawendatu et al., 2026; Rainy et al., 2023). Research in the electronics industry shows that a Generative AI-based framework can reduce processing time by up to 12.5 times, increase throughput by more than ten times, and generate significant operational cost savings every month (Lin and Dang, 2026). In addition, manufacturing simulations show that AI can reduce predictive maintenance time, optimize production scheduling, and increase overall organizational productivity (Rahman et al., 2026).

5. Organizational Competitiveness and Competitive Advantage

Research findings show that AI integration is a key source of organizational competitive advantage. AI enables companies to increase innovation, accelerate market response, optimize business processes, and create competitive differentiation that is difficult for competitors to imitate (AL-Ghamdi, 2026; Lawendatu et al., 2026; Rainy et al., 2023). The implementation of AI-based Enterprise Systems also strengthens industrial competitiveness through improved product quality, continuous innovation, and the organization's ability to systematically carry out digital transformation (Leite et al., 2026). In several studies, AI has even been proven to increase organizational effectiveness, operational flexibility, and accelerate enterprise transformation, resulting in sustainable competitive advantage in the long term (Fei et al., 2025; Gonçalves et al., 2022; Somanathan, 2025).

6. Customer Experience, Customer Engagement, dan Brand Value

In addition to improving internal efficiency, AI also enhances the quality of customer relationships. Integrating AI into CRM leads to personalized service, increased customer satisfaction, successful cross-selling strategies, and faster response times, thereby boosting customer retention (Rainy et al., 2023). Digital transformation in the logistics sector also enhances the customer experience through services that are more responsive, flexible, and focused on customer needs (Iazza et al., 2026). Other studies show that the implementation of AI can strengthen customer engagement, increase customer loyalty, and enhance brand equity as part of creating long-term business value (Fei et al., 2025; Gonçalves et al., 2022).

7. Supply Chain Performance and Organizational Resilience

The implementation of AI also has a significant impact on improving supply chain performance. Integrated enterprise systems support cross-organizational collaboration, real-time information exchange, and more efficient coordination of supply chain activities (Xu, 2011). AI also improves distribution efficiency, enhances logistics visibility, and increases supply chain resilience against global disruptions through the use of blockchain, IoT, and predictive analytics (Iazza et al., 2026). Other studies show that AI helps companies improve financial stability, strengthen organizational resilience against economic and geopolitical crises, and accelerate industrial modernization toward a global digital ecosystem (Trunina et al., 2026).

8. Sustainable Performance and Digital Transformation Performance

The final outcome components most frequently identified were Sustainable Performance and Digital Transformation Performance. Various studies show that AI serves as the primary foundation for the success of sustainable digital transformation through real-time data synchronization, automated data governance, system interoperability, and continuously evolving adaptive learning (Rahman et al., 2026). Modern enterprise systems also contribute to sustainable economic development through efficient use of resources, reduced environmental impact, and increased industrial productivity (Xu, 2011). The implementation of AI supports the achievement of an organization's sustainability goals by improving energy efficiency, reducing carbon emissions, optimizing production, and enhancing the organization's digital resilience, in line with the Sustainable Development Goals (SDGs) (Hidayatullah et al., 2026; Iazza et al., 2026). In addition, various studies show that AI enhances digital transformation performance by improving organizational effectiveness, operational flexibility, organizational learning, enterprise transformation, and the creation of sustainable business value (Fei et al., 2025; Gonçalves et al., 2022; Somanathan, 2025).

DISCUSSION

Business Process Automation in the AI-Driven Enterprise Systems Framework

Business Process Automation (BPA) is a key foundation of the AI-Driven Enterprise Systems (AI-ES) Framework because it enables the transformation of business processes from manual administrative tasks to adaptive, intelligent, and data-driven processes. The integration of Artificial Intelligence (AI), Machine Learning (ML), and Intelligent Process Automation (IPA) means that automation is no longer merely about executing pre-programmed rules, but is capable of learning from data patterns and generating more context-aware decisions (Kalista et al., 2026; Macha, 2025; Udukumburage and Pushpakumara, 2026). This trend indicates that AI is shifting the automation paradigm from rule-based automation toward cognitive automation, which has the ability to learn and adapt to the dynamics of business processes (Coito et al., 2020).

The integration of AI with Robotic Process Automation (RPA) expands the capabilities of traditional automation through the use of machine learning and natural language processing (NLP), enabling the system to understand information derived from unstructured data (Kalista et al., 2026; Udukumburage and Pushpakumara, 2026). Unlike conventional RPA, which can only execute deterministic procedures, Intelligent Automation is capable of identifying new patterns, automatically classifying documents, and generating recommendations for action based on the system's historical experience (Sambamurthy and Tamminedi, 2025). The findings show that AI serves as an intelligence layer that enhances the flexibility of business processes compared to previous-generation automation approaches.

These improvements are evident in financial administration and enterprise document management processes. The integration of NLP and machine learning enables the system to read various formats of invoices, purchase orders, and operational documents without requiring a standardized template. The extracted information is then validated through an intelligent auto-matching mechanism before being automatically processed into financial transactions, thereby reducing human involvement in administrative tasks. As a result, AI not only accelerates business processes but also improves the consistency and accuracy of data processing, as validation is based on continuously evolving historical data (Pakkirisamy, 2025; Tayal, 2026).

Intelligent Automation delivers significant improvements in operational efficiency. AI-based frameworks are reported to achieve automation rates of over 99.8% in certain processes through a combination of workflow automation, predictive analytics, and adaptive learning (Kalista et al., 2026). In addition, the implementation of intelligent automation has proven effective in optimizing resource allocation, accelerating the completion of business processes, and reducing operating costs by minimizing repetitive manual tasks (Margaret, 2026). These findings reinforce the argument that the primary value of AI lies not merely in replacing human jobs, but in enhancing an organization's overall productivity through continuous process automation (Tayal, 2026).

In the context of AI-Driven Enterprise Systems, business process automation also contributes to improving the quality of an organization's decision-making. The integration of predictive analytics, real-time data processing, and self-learning mechanisms enables the system to continuously monitor operational conditions, identify potential disruptions early on, and proactively provide decision recommendations. This capability makes business processes more responsive to changes in the business environment than traditional ERP systems, which generally only generate historical reports.

Nevertheless, the implementation of Intelligent Automation still faces various technical and organizational challenges. The biggest obstacles stem from interoperability issues between enterprise applications, inconsistent data quality, and the complexity of integrating with legacy systems that are still widely used by companies (Coito et al., 2020; Margaret, 2026). In addition to technical aspects, AI governance and explainable AI mechanisms are essential prerequisites for ensuring that the decisions generated by the system can be understood and trusted by users (Guglaani, 2026; Sambamurthy and Tamminedi, 2025). This indicates that the success of AI-ES implementation is determined not only by the sophistication of the algorithms, but also by the organization's readiness to build a data ecosystem and ensure sound governance (Lievano-Martínez et al., 2022).

In addition to technical challenges, the literature also highlights the emergence of sociotechnical challenges during the implementation of intelligent automation. The use of AI in business processes often causes psychological anxiety, as some workers view automation as a threat to their job security (Ghobakhloo et al., 2023). Therefore, the Industry 5.0 paradigm proposes a human-centered AI approach that positions AI as collaborative intelligence or cobots that support human decision-making, rather than completely replacing it. This approach has been proven to increase technology adoption and expedite the digital transformation process when organizations also invest in human resource competency development (Mhaskey, 2024).

Predictive Decision Support in the AI-Driven Enterprise Systems Framework

Predictive Decision Support is one of the most significant transformations in the AI-Driven Enterprise Systems (AI-ES) Framework because it transforms the function of Enterprise Resource Planning (ERP) from a historical reporting system into a predictive and adaptive decision-making platform (Ali and Gang, 2025; AlMahadin, 2025; Khurram et al., 2025). Conventional ERP systems generally still face various limitations, such as fragmented information, data latency, and a limited ability to respond to changes in the business environment in real time (Pohrib et al., 2025; Sinnappan, 2026). These conditions often result in strategic decision-making being reactive, as it relies on historical data that does not adequately reflect current operational conditions.

The integration of Artificial Intelligence (AI) and predictive analytics overcomes these limitations through the use of machine learning, deep learning, neural networks, decision trees, and regression analysis algorithms, which are capable of generating predictions based on both historical and real-time data patterns (Balla et al., 2026). Unlike traditional ERP systems, which only generate operational reports, Intelligent ERP is capable of forecasting demand, analyzing risk, optimizing resource allocation, and automatically generating decision recommendations based on AI model learning. These findings demonstrate that AI not only enhances the analytical capabilities of enterprise systems but also transforms ERP into a decision intelligence platform that supports proactive decision-making (AlMahadin, 2025; Sajja et al., 2025).

These predictive capabilities are further enhanced through the use of an in-memory database combined with deep learning algorithms, enabling the system to process hundreds of thousands of transactions in a very short time to generate instant decision recommendations (Pohrib et al., 2025). This real-time processing capability directly reduces data latency, a major weakness of conventional ERP systems, and enables organizations to obtain relevant information at the moment decisions are made. Thus, AI acts as a mechanism that simultaneously connects operational data with strategic decisions without waiting for the batch processing that occurs in traditional ERP systems (Bonthu, 2025).

The implementation of predictive analytics also results in significant improvements in the quality of organizational decisions. Studies show that integrating AI into ERP can reduce operational inefficiencies by up to 40% and increase sales growth by approximately 25% through improved forecasting accuracy, optimized resource allocation, and improved risk mitigation (Ali and Gang, 2025; Balla et al., 2026). These findings show that the main value of AI is not just increasing computing speed, but producing more accurate business decisions that can strengthen organizational competitiveness in a dynamic business environment.

In the financial sector, Predictive Decision Support capabilities are evolving towards increasingly adaptive systems through the integration of Deep Learning, Bayesian Networks, and Graph Neural Networks (GNN) in the transaction analysis process (Pakkirisamy, 2025). The combination of these various models enables the system to detect deviant transaction patterns in real-time, thereby increasing the effectiveness of the fraud detection system by up to around 60% compared to conventional post-event audit mechanisms (Shaik, 2024). These results show that AI not only functions as a predictive tool, but also as a risk mitigation mechanism that can protect organizations from potential financial losses more quickly and accurately.

The advantages of Intelligent ERP are also reflected in the improved quality of an organization's financial decisions. Compared to traditional ERP, which still relies on manual estimates based on historical trends, Bayesian algorithms and machine learning can improve the accuracy of financial projections by up to 27%, speed up the decision-making process by approximately 42%, and reduce cash flow forecast deviation by up to 37% (Pakkirisamy, 2025). This increase has strategic implications in the form of optimizing working capital allocation, increasing the company's liquidity resilience, and the organization's ability to respond to market changes more adaptively.

Despite its numerous advantages, implementing AI-based predictive analytics still faces a number of challenges. Integrating AI with legacy ERP systems requires high architectural interoperability, a mature data infrastructure, and complex integration mechanisms, often presenting implementation barriers for many organizations. In addition, the effectiveness of predictive models is greatly influenced by the quality of the data used, so that the problem of data inconsistency, missing values, and information privacy issues are still the main challenges in building an accurate and reliable prediction system. Therefore, the success of implementing Predictive Decision Support is not only determined by the sophistication of the AI algorithm, but also by the organization's readiness to build quality data governance.

In addition to technical factors, organizational investment in human resource competency development is also a critical factor in the success of Intelligent ERP implementation. High implementation costs and a limited workforce with expertise in AI, data science, and enterprise architecture remain obstacles to the adoption of Predictive Decision Support across various industry sectors. This condition shows that the transformation towards AI-Driven Enterprise Systems must be viewed as a comprehensive organizational transformation that includes technological readiness, data quality, and increasing human resource capabilities simultaneously.

Supply Chain Optimization through Adoption of AI-Driven Enterprise Systems (AI-ES) Framework

The implementation of AI-Driven Enterprise Systems (AI-ES) demonstrates a paradigm shift in supply chain management from a reactive approach to an adaptive, predictive system capable of real-time decision-making. The results of this study's literature synthesis indicate that the integration of Artificial Intelligence into Enterprise Systems enables the automation of demand planning, inventory control, logistics management, and supplier risk mitigation through continuous data analysis integrated with ERP, IoT, and cloud computing platforms.

The main capability of AI-ES is seen in increasing the accuracy of demand forecasting through the use of machine learning algorithms that are able to study historical patterns and market demand dynamics simultaneously. Unlike conventional forecasting methods that rely on linear statistical approaches, AI-based predictive models produce more adaptive demand estimates, thereby reducing forecasting errors, optimizing inventory levels, and significantly reducing stockouts and overstocks. This is consistent with various studies reporting increased forecasting accuracy through XGBoost, Random Forest, and Deep Learning models, resulting in more efficient inventory turnover and higher operational stability (Mohammad et al., 2024; Selvamuthu et al., 2026; Suura et al., 2026).

AI integration with ERP enables companies to monitor inventory in real time, dynamically predict material requirements, and generate automated ordering recommendations based on changes in demand and production capacity. Scopus literature shows that adaptive learning mechanisms improve inventory management efficiency, reduce operational costs, and increase inventory turnover by up to 61.9% compared to conventional approaches (Mohammad et al., 2024; Sayeed et al., 2026; Selvamuthu et al., 2026). Furthermore, AI-ES optimizes logistics through the integration of Reinforcement Learning, Genetic Algorithms, and spatial analytics to adaptively determine distribution routes, simultaneously considering traffic conditions, fleet capacity, weather, and customer demand. This approach has been proven to reduce delivery delays by 30–40%, reduce transportation costs by up to 29.2%, and improve distribution accuracy and fuel efficiency (Meng et al., 2026).

The results of the literature synthesis also indicate that AI-Driven Enterprise Systems contribute directly to supply chain cost efficiency through the integration of demand prediction functions, inventory optimization, and operational decision automation. Various studies report that the application of AI in the supply chain can reduce total operational costs by up to 34.8%, increase Return on Investment (ROI), and reduce resource waste due to inaccurate inventory and distribution planning. Furthermore, the implementation of AI-ES strengthens supply chain agility through the system's ability to quickly detect changes in the business environment and automatically adjust decisions. The integration of the Internet of Things (IoT), Digital Twin, and real-time analytics enables organizations to gain complete visibility into supply chain activities so that operational disruptions can be identified early and proactively mitigated (Bhat et al., 2025; Harish et al., 2024; Mangual et al., 2025). Various studies have shown that the combination of AI with Digital Twin results in increased organizational adaptability to market changes and distribution disruptions through dynamic, data-driven decision-making processes.

Real-Time Data Integration in Artificial Intelligence-Driven Enterprise Systems

Real-time data integration is a key foundation of AI-Driven Enterprise Systems (AI-ES) because it enables all enterprise components to access up-to-date information to support adaptive decision-making. A review of the literature indicates that continuous data integration from IoT sensors, enterprise applications, and various operational data sources generates situational intelligence capable of enhancing an organization’s ability to respond quickly and accurately to changes in the business environment. This approach overcomes the limitations of conventional enterprise systems, which still rely on periodic data processing and thus often result in information latency and delays in decision-making (Prithiviraj et al., 2025; Veernapu et al., 2026). These findings are also consistent with the results of research on Layer 3, which show that data synchronization capabilities, interoperability, and a continuous data lifecycle are prerequisites for the development of adaptive business intelligence in Intelligent Enterprise Systems (Lawendatu et al., 2026; Leite et al., 2026; Rahman et al., 2026).

Technologies such as Apache Spark, Apache Kafka, and Apache Flink enable continuous, low-latency data streaming, allowing enterprise systems to process millions of operational data points in a very short time without compromising system performance. This distributed stream processing approach supports enterprise scalability as data volumes continue to grow and enables the ongoing development of adaptive learning systems (Hameed et al., 2026; Prithiviraj et al., 2025). The analyzed research findings also show that the implementation of a cloud platform, PostgreSQL, REST APIs, and an ERP dashboard forms a data synchronization mechanism capable of maintaining the consistency of information across organizational units in real time.

Although it offers significant benefits, the implementation of real-time data integration still faces fairly complex challenges. The main obstacles include low interoperability between platforms, the presence of legacy systems, the lack of uniform data exchange standards, and increased cybersecurity risks resulting from continuous data exchange. Furthermore, organizational readiness and human resource competencies remain key determinants of the successful implementation of AI-Driven Enterprise Systems, as digital transformation requires not only technological readiness but also the organizational culture's readiness to fully adopt data-driven business processes. These findings are further supported by a literature review indicating that technological readiness, integration capability, governance, and enterprise architecture are key determinants in ensuring the successful implementation of AI in modern enterprise environments.

CONCLUSION

This study develops a conceptual framework for Artificial Intelligence-Driven Enterprise Systems (AI-ES Framework) through a Systematic Literature Review (SLR) approach to explain how artificial intelligence transforms enterprise systems from conventional operational platforms into intelligent, adaptive, and decision-oriented systems. The results of the literature synthesis indicate that this transformation is built through four main, mutually integrated layers: the AI Technology Layer, the Intelligent Enterprise System Layer, the Business Intelligence Layer, and the Business Outcome Layer.

At the first layer, various AI technologies such as Machine Learning, Deep Learning, Natural Language Processing, Large Language Models, and Predictive Analytics along with supporting technologies like IoT, Big Data, Blockchain, and Cloud Computing, form the core foundation for building enterprise analytics and automation capabilities. Next, these technologies are implemented in the Intelligent Enterprise System Layer through the integration of ERP, CRM, PLM, MES, Enterprise Architecture, cloud platforms, workflow automation, and various interoperability mechanisms that enable the creation of a more adaptive, integrated, and data-driven enterprise system.

These capabilities are then translated within the Business Intelligence Layer into various intelligent business functions such as business process automation, predictive analytics, real-time data synchronization, supply chain optimization, data visualization, and AI-based decision-making. A review of the literature indicates that AI not only improves operational efficiency but also strengthens an organization's ability to make predictions, manage risk, optimize resources, and respond more quickly to the dynamics of the business environment.

Ultimately, the implementation of AI-Driven Enterprise Systems yields a range of strategic impacts on the Business Outcome Layer, including improvements in operational excellence, business agility, innovation capability, organizational effectiveness, customer engagement, competitive advantage, and sustainable performance. Thus, this study confirms that the primary value of AI stems not only from the capabilities of its algorithms, but also from an organization's success in integrating technology, enterprise systems, business processes, and organizational capabilities into a single, mutually supportive digital ecosystem.

This research contributes by proposing an AI-Driven Enterprise Systems Framework that provides a holistic perspective on the relationship between Artificial Intelligence capabilities, Enterprise Systems integration, Business Intelligence, and organizational digital transformation performance. This conceptual framework can serve as a reference for academics and practitioners in designing, implementing, and evaluating AI adoption as an organizational transformation strategy, not just a technology implementation. The research results emphasize the importance of strengthening digital infrastructure, system interoperability, data governance and quality, AI integration with enterprise platforms (ERP, CRM, SCM), as well as enhancing digital competency and transparent AI governance to support sustainable implementation. Furthermore, further research is recommended to validate this framework through empirical approaches, such as SEM or PLS-SEM, and explore the utilization of new generation AI technologies, including Generative AI, AI Agents, Digital Twins, Explainable AI (XAI), Federated Learning, and Multi-Agent Systems, taking into account differences in characteristics across industries as well as aspects of security, privacy, ethics, sustainability, and measuring the maturity level of AI-based digital transformation.

REFERENCES

Abuowaida, S., Al-Arqan, A., & Al-Mhasneh, K. (2025). Artificial Intelligence and Organizational Decision-Making: Transforming Strategic Choices in the Era of Digital Intelligence. *2025 International Conference on Decision Aid Sciences and Applications (DASA)*, 2532–2538. https://doi.org/10.1109/DASA68193.2025.11498922

AL-Ghamdi, S. A. (2026). Integrating AI, IoT, and blockchain into enterprise architecture: A model of readiness, integration capability, and value creation. *International Journal of Advanced and Applied Sciences, 13*(3), 86–94. https://doi.org/10.21833/ijaas.2026.03.009

Ali, H. B. Y., & Gang, Z. J. (2025). Predictive Analytics Model for AI-Enhanced Decision Support in Corporate Management. *Journal of Computers, Mechanical and Management, 4*(6), 48–56. https://doi.org/10.57159/jcmm.4.6.25232

Aliverdiyev, S. (2025). The Impact of Artificial Intelligence on the Digital Transformation of Corporate Information Systems. *Scientific Work, Special (Issue)*, 46–53. https://doi.org/10.36719/2663-4619/116/46-53

AlMahadin, G. (2025). Adaptive AI-Driven Enterprise Resource Planning for Scalable and Real-Time Strategic Decision Making. *International Journal of Advanced Computer Science and Applications, 16*(7). https://doi.org/10.14569/IJACSA.2025.0160758

Bala, H., Hossain, M. M., Bhagwatwar, A., & Feng, X. (2021). Ownership and governance, scope, and empowerment: how does context affect enterprise systems implementation in organisations in the Arab World? *European Journal of Information Systems, 30*(4), 425–451. https://doi.org/10.1080/0960085X.2020.1803775

Balakayeva, G., Zhanuzakov, M., Zhapbasbayev, U., & Nurlybayeva, K. (2025). An intelligent enterprise system with processing and verification of business documents using big data and AI. *Journal of Intelligent Systems, 34*(1). https://doi.org/10.1515/jisys-2024-0446

Balla, R. T., Padmanabham, S., Bhandari, R. S., Kumar, V., & Singh, G. (2026). AI-Driven Optimization of Enterprise Resource Planning Systems: An SEM-Based Analysis of Decision-Making Effectiveness. *2026 5th International Conference on Innovative Practices in Technology and Management (ICIPTM)*, 1–6. https://doi.org/10.1109/ICIPTM69057.2026.11465533

Beth, B. D. C., Laksana, R. P., Sekti, B. A., Asri, J. S., & Wahyu, S. (2026). Introduction to AI in Supply Chain Management (pp. 1676–1698). https://doi.org/10.4018/406745

Bhat, D., Thorat, N., H. C, S. M., B. B, G., Sutaria, K., & Kannan, S. (2025). Digital Transformation in the Supply Chain: Leveraging AI and Blockchain for Operational Efficiency. *2025 International Conference on Intelligent Communication Networks and Computational Techniques (ICICNCT)*, 1–6. https://doi.org/10.1109/ICICNCT66124.2025.11233126

Bonthu, C. (2025). Real-Time Data Processing in ERP Systems: Benefits and Challenges. *Journal of Information Systems Engineering and Management, 10*(45s), 409–430. https://doi.org/10.52783/jisem.v10i45s.8889

Chen, S.-L., Chen, Y.-Y., & Hsu, C. (2014). A New Approach to Integrate Internet-of-Things and Software-as-a-Service Model for Logistic Systems: A Case Study. *Sensors, 14*(4), 6144–6164. https://doi.org/10.3390/s140406144

Chu, K.-M. (2026). Human AI Co-Intelligence in Smart SMEs: Integrating Generative AI and ERP-Driven Decision Intelligence in Taiwan's Precision Manufacturing Sector. *Expert Systems with Applications, 321*, 132373. https://doi.org/10.1016/j.eswa.2026.132373

Clemens, F., Willemsen, F., Mütze-Niewöhner, S., & Schuh, G. (2023). Development of a Task Model for Artificial Intelligence-Based Applications for Small and Medium-Sized Enterprises. *In IFIP Advances in Information and Communication Technology* (pp. 528–542). https://doi.org/10.1007/978-3-031-43662-8_38

Coito, T., Martins, M. S. E., Viegas, J. L., Firme, B., Figueiredo, J., Vieira, S. M., & Sousa, J. M. C. (2020). A Middleware Platform for Intelligent Automation: An Industrial Prototype Implementation. *Computers in Industry, 123*, 103329. https://doi.org/10.1016/j.compind.2020.103329

Dziembek, D., & Turek, T. (2025). A Model for Integrating Artificial Intelligence with ERP Systems – Towards Autonomous Business Management Systems. *Procedia Computer Science, 270*, 6260–6269. https://doi.org/10.1016/j.procs.2025.10.096

Ergün, H. (2026). Digital Transformation and the Evolution of Professional Identity: A Qualitative Study on the Perceptions of Office Management and Secretarial Students. *Human Behavior and Emerging Technologies,* *2026*(1). https://doi.org/10.1155/hbe2/3365394

Evangeline, S. I. (2025). AI for Business Management. *In Transforming Business Through Digital Sustainability Models* (pp. 411–426). IGI Global. https://doi.org/10.4018/979-8-3373-0608-7.ch018

Fei, Y.-M., Liou, J.-C., & Sun, P. J. (2025). Evaluating the dual impact of AI and RPA on sustainability and brand equity: A case study of digital transformation in Taiwan's service sector. *Cleaner Engineering and Technology, 29*, 101106. https://doi.org/10.1016/j.clet.2025.101106

Galster, M., & Avgeriou, P. (2015). An industrial case study on variability handling in large enterprise software systems. *Information and Software Technology*, 60, 16–31. https://doi.org/10.1016/j.infsof.2014.12.003

Ghobakhloo, M., Asadi, S., Iranmanesh, M., Foroughi, B., Mubarak, M. F., & Yadegaridehkordi, E. (2023). Intelligent automation implementation and corporate sustainability performance: The enabling role of corporate social responsibility strategy. *Technology in Society, 74*, 102301. https://doi.org/10.1016/j.techsoc.2023.102301

Gonçalves, M. J. A., da Silva, A. C. F., & Ferreira, C. G. (2022). The Future of Accounting: How Will Digital Transformation Impact the Sector? *Informatics, 9*(1), 19. https://doi.org/10.3390/informatics9010019

Gorkhali, A., & Xu, L. Da. (2019). Enterprise Architecture, Enterprise Information Systems and Enterprise Integration: A Review Based on Systems Theory Perspective. *Journal of Industrial Integration and Management, 04*(02), 1950001. https://doi.org/10.1142/S2424862219500015

Guglaani, A. (2026). A2G Framework: A Practitioner-Validated Hybrid Approach for Deploying Explainable Artificial Intelligence and Intelligent Automation in Family Businesses and Mid-Sized Enterprises. *2026 International Conference on Electrical/Electronics, Robotics, Artificial Intelligence, and Informatics (ICERAI)*, 1–6. https://doi.org/10.1109/ICERAI69511.2026.11494578

Hameed, S., Karagoz, S., Ozdemir, A., Khosravi, A., Fatima, R., Zulqarnain, & Aitkaliyeva, G. (2026). Real-time decision support systems in chemical and process engineering. *In Artificial Intelligence in Chemical Engineering* (pp. 313–348). Elsevier. https://doi.org/10.1016/B978-0-443-34076-5.00021-3

Harish, Kotehal, P., Sandesh, M. M., Reddy, Y. M., & Roopa. (2024). Artificial Intelligence in Supply Chain Management: Trends and Implications. *Nanotechnology Perceptions, 20*(S7). https://doi.org/10.62441/nano-ntp.v20iS7.91

Harmon, J., Lazaros, E. J., Allam, H., Davison, C. B., & Truell, A. D. (2025). The growing adoption of artificial intelligence (AI) to drive innovation, resulting in enhanced competitiveness. *Issues In Information Systems*. https://doi.org/10.48009/3_iis_2025_2025_122

Hidayatullah, A. A., Purnomo, H., Soewardi, H., & Widodo, I. D. (2026). ERP and Artificial Intelligence as Transformative Technologies for SME Sustainability: A Socio-Technical Systems Perspective. *International Journal of Sustainable Development and Planning, 21*(3), 1097–1110. https://doi.org/10.18280/ijsdp.210312

Huiping, C. (2009). An Integration Framework of ERM, SCM, CRM. *2009 International Conference on Management and Service Science*, 1–4. https://doi.org/10.1109/ICMSS.2009.5301692

Hundekari, S., Praveen, R., Shrivastava, A., Hwsein, R. R., Bansal, S., & Kansal, L. (2025). Impact of AI on Enterprise Decision-Making: Enhancing Efficiency and Innovation. *2025 International Conference on Engineering, Technology & Management (ICETM)*, 1–5. https://doi.org/10.1109/ICETM63734.2025.11051526

Hussein, B., Yildrim, G., & Wolff, C. (2026). A Framework for Implementing AI-based Technologies To Enhance Knowledge Management Processes. *Procedia Computer Science, 278*, 566–573. https://doi.org/10.1016/j.procs.2026.03.025

Iazza, W., El-Aissam, I., Aba-Talib, K., Saloumi, S., & Zouine, A. (2026). Impact of Digital Transformation on Logistics: A Systematic and Bibliometric Literature Review. *Ianna Journal of Interdisciplinary Studies, 8*(2), 670–687. https://doi.org/10.5281/zenodo.20455663

Ilham, R., Suwanda, R. P., Suryaningrum, N. M., & Wibawa, I. M. L. (2026). Impact of Digital Transformation on Organizational Agility and Business Performance in Medium Sized Enterprise. *International Journal of Business, Law, and Education, 7*(1), 166–176. https://doi.org/10.56442/ijble.v7i1.1343

Jansen, S. (2017). Bias within systematic and non- systematic literature reviews: the case of the Balanced Scorecard. *University of Twente*.

Kalista, A., Abdulwahhab, R. I., Fadily, F., & Fadhil, A. (2026). Intelligent Business Process Management Systems with AI Augmentation and Framed Autonomy. *In STEAM-H: Science, Technology, Engineering, Agriculture, Mathematics and Health* (pp. 267–277). https://doi.org/10.1007/978-3-032-19130-4_22

Khurram, S., Hussain, D., Ahmed, B., & Khan, S. (2025). Revolutionizing Strategic Decision-Making: The Transformative Impact of AI-Enhanced ERP Systems. *2025 5th International Conference on Digital Futures* *and Transformative Technologies (ICoDT2)*, 1–8. https://doi.org/10.1109/ICoDT269104.2025.11360744

Kim, D. J., Locke, S., Chen, T.-H. P., Toma, A., Sporea, S., Weinkam, L., & Sajedi, S. (2023). Challenges in Adopting Artificial Intelligence Based User Input Verification Framework in Reporting Software Systems. *2023 IEEE/ACM 45th International Conference on Software Engineering: Software Engineering in Practice (ICSE-SEIP),* 99–109. https://doi.org/10.1109/ICSE-SEIP58684.2023.00014

Lawendatu, A. S., Hidayat, F., Radhia, F., & Hartono, S. (2026). Adopting Artificial Intelligence in ERP Systems as an Innovation to Support Business Growth: A Systematic Literature Review. *Journal of Computer Science, 22*(3), 947–959. https://doi.org/10.3844/jcssp.2026.947.959

Leite, J. C., do Nascimento, M. M., de Almeida, A. A. S., de Souza, M. P. de S., Martins, L. da S., da Silva, P. R. F., & Brasil, M. H. G. (2026). Development of an Integrated Intelligent Manufacturing System Utilizing IoT and Data Mining for the Digital Transformation of Industry 4.0. *ITEGAM- Journal of Engineering and Technology for Industrial Applications (ITEGAM-JETIA), 12*(59), 1059–1070. https://doi.org/10.5935/jetia.v12i59.4495

Lievano-Martínez, F. A., Fernández-Ledesma, J. D., Burgos, D., Branch-Bedoya, J. W., & Jimenez-Builes, J. A. (2022). Intelligent Process Automation: An Application in Manufacturing Industry. *Sustainability, 14*(14), 8804. https://doi.org/10.3390/su14148804

Lin, Y.-C., & Dang, J.-F. (2026). From product specifications to smart manufacturing: Generative AI-driven process innovation for BOM digitization and its applications. *Advanced Engineering Informatics, 71*, 104451. https://doi.org/10.1016/j.aei.2026.104451

Macha, K. B. (2025). AI in Hyper Automation: From RPA to Intelligent Automation Ecosystems. *2025 Second International Conference on Networks and Soft Computing (ICNSoC)*, 360–365. https://doi.org/10.1109/ICNSoC66817.2025.00074

Mangual, A., Elhidaoui, S., & Benhida, K. (2025). Leveraging Artificial Intelligence for Supply Chain Optimization: A Systematic Analysis of Implementation Challenges and Opportunities Using the Analytic Hierarchy Process (AHP). *Industrial Engineering & Management Systems, 24*(1), 81–103. https://doi.org/10.7232/iems.2025.24.1.081

Margaret, S. (2026). Role of Process Discovery and Optimization in Hyperautomation. In Implementing Hyper Automation: Strategies, Best Practices and Case Studies (pp. 60–95). *Bentham Science Publishers*. https://doi.org/10.2174/9798898813000126010007

Martin, E.-L., & Nair, P. (2024). Revolutionizing Supply Chain Optimization with AI- Driven Predictive Analytics. *Synergy: Cross-Disciplinary Journal of Digital Investigation, 2*(12), 31–45. http://eprints.umsida.ac.id/15852/1/Revolutionizing Supply Chain Optimization.pdf

Maruf, A. Al. (2025). A Systematic Review of ERP-Integrated Decision Support Systems for Financial And Operational Optimization in Global Retails Business. *American Journal of Interdisciplinary Studies, 06*(01), 236–262. https://doi.org/10.63125/qgbrmf24

Meng, T., Cui, H., Wang, W., & Yang, S. (2026). Dynamic Scheduling Model and Simulation Analysis of an AI-Driven Supply Chain Optimization Framework. *International Journal of Information Systems and Supply Chain Management, 19*(1), 1–33. https://doi.org/10.4018/IJISSCM.400899

Mhaskey, S. V. (2024). Integration of Artificial Intelligence (AI) in Enterprise Resource Planning (ERP) Systems: Opportunities, Challenges, and Implications. *International Journal of Computer Engineering in Research Trends, 11*(12), 1–9. https://doi.org/10.22362/ijcert/2024/v11/i12/v11i1201

Mohammad, A. A. S., Khanfar, I. A. ., Al Oraini, B., Vasudevan, A., Suleiman, I. M., & Fei, Z. (2024). Predictive analytics on artificial intelligence in supply chain optimization. *Data and Metadata, 3*, 395. https://doi.org/10.56294/dm2024395

Munir, H. F. I., & Kristian, W. (2025). The Role of Artificial Intelligence in Accelerating Digital Transformation in Manufacture Industries. *2025 IEEE 15th Symposium on Computer Applications & Industrial Electronics (ISCAIE)*, 219–223. https://doi.org/10.1109/ISCAIE64985.2025.11080965

Pakkirisamy, S. (2025). AI-driven cloud ERP: The next frontier in predictive financial management. *World Journal of Advanced Research and Reviews, 26*(1), 4160–4169. https://doi.org/10.30574/wjarr.2025.26.1.1516

Pańkowska, M. (2017). Enterprise Architecture Context Analysis Proposal. *In Lecture Notes in Information Systems and Organisation* (pp. 117–134). https://doi.org/10.1007/978-3-319-52593-8_8

Parveen Roja, M., Kuppam, M., Koduru, S. K. R., Byloppilly, R., Trivedi, S. D., & Rajest, S. S. (2024). An Aid of Business Intelligence in Retailing Services and Experience Using Artificial Intelligence. *In Cross-Industry AI Applications* (pp. 14–30). https://doi.org/10.4018/979-8-3693-5951-8.ch002

Pohrib, S.-D., Goga, A.-S., & Pîsla, A. (2025). Smart ERP Systems – From Data to Decisions. *Proceedings of the International Conference on Business Excellence, 19*(1), 380–401. https://doi.org/10.2478/picbe-2025-0032

Prithiviraj, A., Selvameena, R., & Babu, T. (2025). Decision-Making in Automotive Working Employee Safety Projects Using AI With IoT-Driven Analytics Using Big Data. *In AI's role in enhanced automotive safety* (pp. 75–90). https://doi.org/10.4018/979-8-3373-0442-7.ch006

Rahman, M., Alam, M. S., Al Sany, S. M. A., & Nahar, S. (2026). Enterprise AI Driven Data Management Framework for Cross Industry Decision Intelligence and Operational Optimization. https://doi.org/10.2139/ssrn.6330258

Rainy, T. A., Goswami, D., Rabbi, M. S., & Maruf, A. Al. (2023). A Systematic Review of Ai-Enhanced Decision Support Tools in Information Systems: Strategic Applications in Service-Oriented Enterprises and Enterprise Planning. *Review of Applied Science and Technology, 02*(01), 26–52. https://doi.org/10.63125/73djw422

Rizana, A. F., Wiratmadja, I. I., & Akbar, M. (2025). Exploring Capabilities for Digital Transformation in the Business Context: Insight from a Systematic Literature Review. *Sustainability, 17*(9), 4222. https://doi.org/10.3390/su17094222

Sahara, C. R., & Aamer, A. M. (2022). Real-time data integration of an internet-of-things-based smart warehouse: a case study. *International Journal of Pervasive Computing and Communications, 18*(5), 622–644. https://doi.org/10.1108/IJPCC-08-2020-0113

Sajja, J. W., Komarina, G. B., & Choppa, N. K. R. (2025). Enterprise Data Transformation in the Era of S/4HANA: Real-World Cloud Migration Architecture, Governance Strategies, and Lessons from the Field. *World Journal of Advanced Research and Reviews, 26*(2), 3596–3619. https://doi.org/10.30574/wjarr.2025.26.2.2038

Sambamurthy, P. K., & Tamminedi, V. (2025). Evolving Software Engineering Practices in the Era of AI-Driven Automation. *2025 International Conference on Computer and Applications (ICCA)*, 1–6. https://doi.org/10.1109/ICCA66035.2025.11430882

Sayeed, N., Saha, U. S., Karim, F., Mustafizur, M., Muhive Uddin, S. M., & Asikur Rahman Chy, M. (2026). Artificial Intelligence Models for End-to-End Supply Chain Optimization. *2026 IEEE International Conference for Convergence in Computing Technology (I3CTCON)*, 1–8. https://doi.org/10.1109/I3CTCON68242.2026.11507407

Selvamuthu, C. M., Panicker, M. S. B., P., R. V., D., A., S., H. G., & B., K. K. (2026). AI-Driven Supply Chain Optimization with Predictive Analytics for Enhanced Efficiency and Scalability in E-Commerce. *2026 13th International Conference on Computing for Sustainable Global Development (INDIACom)*, 1–6. https://doi.org/10.23919/INDIACom70271.2026.11526274

Shaik, M. S. (2024). Impact of AI on Enterprise Cloud-Based Integrations and Automation. *International Journal of Scientific Research in Computer Science, Engineering and Information Technology, 10*(6), 1393–1401. https://doi.org/10.32628/CSEIT241061180

Sinnappan, G. S. (2026). Artificial Intelligence-Driven Decision Making in Modern Business Intelligence. *In Harnessing AI and Predictive Analytics for Decision-Making and Competitive Advantage* (pp. 95–124). https://doi.org/10.4018/979-8-3373-3648-0.ch004

Sira, M. (2025). A gap analysis framework for enterprise AI implementation. *Production Engineering Archives, 31*(3), 291–310. https://doi.org/10.30657/pea.2025.31.28

Somanathan, D. S. (2025). Driving SCM and HR Transformation through AI, Transformational Leadership, and Innovation in Digital Enterprise Systems. *Archives for Technical Sciences, 34*(3), 1048–1059. https://doi.org/10.70102/afts.2025.1834.1048

Sun, Y. (2021). 3D CAD Information System Integration Based on the Private Cloud Platform. *Computer-Aided Design and Applications, 19*(S6), 1–12. https://doi.org/10.14733/cadaps.2022.S6.1-12

Suura, S. R., Chava, K., Chakilam, C., Malempati, M., & Nuka, S. T. (2026). Revolutionizing Retail Supply Chains with AI and Cloud Computing: A Big Data Approach to Demand Forecasting and Logistics Optimization. *In Lecture Notes in Networks and Systems* (pp. 271–283). https://doi.org/10.1007/978-3-032-08243-5_25

Syed, S. A. (2025). Integrating Digital Transformation and Sustainability for Operational Excellence in Procurement and Supply Chain Management: An Empirical Framework for the Middle East Region. *International Journal of Advanced Engineering Research and Science, 12*(12), 73–79. https://doi.org/10.22161/ijaers.1212.7

Tayal, C. (2026). Assessing the Scope of Optimising Operational Roles Through Intelligent Automation Frameworks. *2026 IEEE 16th Annual Computing and Communication Workshop and Conference (CCWC)*, 0063–0068. https://doi.org/10.1109/CCWC67433.2026.11393895

Thambireddy, S., Reddy Bussu, V. R., Madathala, H., Mane, V., & Inamdar, C. (2025). AI-Enabled SAP Enterprise

Systems: A Comprehensive Business Use Case Survey. *2025 5th International Conference on Soft Computing for Security Applications (ICSCSA)*, 1045–1052. https://doi.org/10.1109/ICSCSA66339.2025.11170704

Tranfield, D., Denyer, D., & Smart, P. (2003). Towards a Methodology for Developing Evidence-Informed Management Knowledge by Means of Systematic Review. British Journal of Management, 14(3), 207–222. https://doi.org/10.1111/1467-8551.00375

Trunina, I. M., Moroz, O. V, & Bilyk, M. Y. (2026). Artificial intelligence, ERP and firm performance: econometric evidence from Ukrainian industry. *Naukovyi Visnyk Natsionalnoho Hirnychoho Universytetu, 3*, 254–261. https://doi.org/10.33271/nvngu/2026-3/254

Udukumburage, P., & Pushpakumara, C. (2026). Gap Analysis of the Implementation of Intelligent Process Automation in the Industrial Context in Sri Lanka – A Systematic Literature Review. *Advances in Science and Technology*, 61–69. https://doi.org/10.4028/p-un4Vn8

Vasilev, J. (2014). The change from ERP II to ERP III systems. *3rd International Conference on Application of Information and Communication Technology and Statistics in Economy and Education (ICAICTSEE 2013)*. https://doi.org/10.13140/2.1.5109.7609

Veernapu, K. K., Patil, B. K., Tharayil, A. S., Sindhura, C. ., Andy, A., Budhewar, A., Somwanshi, S. K., Kavya, K., Bharadwaj, M., & Raj, P. (2026). Real-time AI in Clinical Decision Support. *In Revolutionizing Drug Research and Personalized Medicine Through AI and Machine Learning* (pp. 431–452). https://doi.org/10.4018/979-8-3373-6400-1.ch015

Villafuerte, C., Moncayo, M., & Oñate, W. (2026). RAMI 4.0 Architecture for Industrial Traceability with Artificial Intelligence and Integrated Security. *Automation, 7*(3), 72. https://doi.org/10.3390/automation7030072

Wang, F., Yao, B., Lu, Y., & Wu, J. (2025). Towards Intelligent Enterprises: AI-Enabled Innovation in Family Businesses. *Proceedings of the 2025 2nd International Conference on Artificial Intelligence and Future Education*, 69–74. https://doi.org/10.1145/3785987.3785998

Wilamowski, B. M. (2005). Welcome to the IEEE Transactions on Industrial Informatics, a New Journal of the Industrial Electronics Society. *IEEE Transactions on Industrial Informatics, 1*(1), 1–2. https://doi.org/10.1109/TII.2005.845249

Xu, L. Da. (2011). Enterprise Systems: State-of-the-Art and Future Trends. *IEEE Transactions on Industrial Informatics, 7*(4), 630–640. https://doi.org/10.1109/TII.2011.2167156

Yu, S., & Osathanunkul, K. (2023). Technology Issues Which Prevent Implementation of Enterprise Resource Planning Systems in LDCs' Organizations. *2023 7th International Conference on Information Technology (InCIT)*, 277–280. https://doi.org/10.1109/InCIT60207.2023.10412894