



Intelligent Decision Support Systems for Enterprise Modernization using Generative AI Predictive Modeling and Process Automation

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ABSTRACT: learning algorithms, and generative AI capabilities to transform raw enterprise data into actionable insights, automated recommendations, and adaptive workflows. Generative AI enhances decision support by producing contextual insights, scenario simulations, and natural language explanations, enabling decision-makers to interpret complex data more effectively. Predictive modeling further strengthens these systems by forecasting trends, identifying risks, and optimizing resource allocation across business functions. Process automation, including robotic process automation and intelligent workflow orchestration, ensures seamless execution of decisions with minimal human intervention. Together, these technologies create a unified framework for intelligent enterprise modernization that improves responsiveness, reduces operational inefficiencies, and supports data-driven strategic planning. However, challenges such as model transparency, data governance, integration complexity, and ethical concerns remain significant barriers. This study explores the architectural and conceptual foundations of intelligent decision support systems in enterprise environments. A qualitative research methodology based on systematic literature review and conceptual synthesis is employed. Findings indicate that integrating generative AI, predictive modeling, and automation significantly enhances enterprise decision intelligence and modernization outcomes.

KEYWORDS: Intelligent decision support systems, generative AI, predictive modeling, process automation, enterprise modernization, machine learning, robotic process automation, decision intelligence, digital transformation, workflow automation, enterprise analytics, AI governance, data-driven decision-making, intelligent systems, business intelligence

I. INTRODUCTION

Modern enterprises operate in increasingly complex and data-intensive environments where timely and accurate decision-making is critical for maintaining competitiveness and operational efficiency. Traditional decision support systems were primarily designed to assist managers with structured reporting and historical data analysis. However, these systems often lack the ability to process large-scale real-time data, generate predictive insights, or adapt dynamically to changing business conditions. As a result, organizations are increasingly adopting Intelligent Decision Support Systems (IDSS) that leverage advanced technologies such as Generative Artificial Intelligence, predictive modeling, and process automation to enhance decision-making capabilities.

Generative AI has introduced a transformative shift in enterprise decision support by enabling systems to generate contextual insights, natural language explanations, and scenario-based simulations. Unlike traditional analytics tools, generative models can synthesize complex datasets and produce human-readable outputs that assist decision-makers in understanding patterns, risks, and opportunities. This capability significantly improves interpretability and accessibility of enterprise data.

Predictive modeling further enhances decision support systems by enabling organizations to forecast future trends, identify potential risks, and optimize resource allocation. Machine learning algorithms analyze historical and real-time data to detect patterns and generate predictive insights that support proactive decision-making. This allows enterprises to anticipate market changes, customer behavior, and operational bottlenecks before they occur.

Process automation plays a critical role in translating decisions into action. Technologies such as robotic process automation and intelligent workflow systems enable enterprises to automate repetitive tasks, streamline business processes, and ensure consistent execution of decisions across organizational functions. When combined with AI-driven insights, automation creates a seamless decision-to-execution pipeline.



Despite these advancements, organizations face challenges related to data governance, model transparency, system integration, ethical considerations, and algorithmic bias. Ensuring responsible and secure implementation of intelligent decision support systems is essential for sustainable enterprise modernization.

This study explores how generative AI, predictive modeling, and process automation collectively contribute to intelligent decision support systems and drive enterprise modernization in complex digital environments.

II. LITERATURE REVIEW

Existing literature on decision support systems highlights their evolution from rule-based systems to advanced AI-driven platforms. Early systems focused on structured data analysis and static reporting, providing limited flexibility in dynamic business environments. With the rise of big data and machine learning, decision support systems have become more adaptive and predictive.

Generative AI has emerged as a significant advancement in enterprise analytics. Research shows that generative models, including large language models, can synthesize complex datasets, generate insights, and provide natural language explanations that enhance decision interpretability. Studies indicate that generative AI improves decision-making speed and quality by reducing cognitive load on human users.

Predictive modeling has long been a core component of enterprise analytics. Machine learning techniques such as regression analysis, classification, clustering, and deep learning are widely used for forecasting demand, detecting anomalies, and optimizing operations. Literature emphasizes that predictive models significantly improve business planning and risk management capabilities.

Process automation, particularly robotic process automation, has been extensively studied in the context of enterprise efficiency. RPA enables organizations to automate repetitive and rule-based tasks, reducing operational costs and improving accuracy. Recent research highlights the integration of AI with automation systems to create intelligent workflows capable of adaptive execution.

However, literature also identifies challenges associated with intelligent decision support systems. These include lack of transparency in AI models, integration difficulties with legacy systems, data privacy concerns, and ethical risks related to automated decision-making. Researchers emphasize the importance of explainable AI and robust governance frameworks to ensure responsible deployment.

Overall, existing studies suggest that combining generative AI, predictive modeling, and process automation significantly enhances decision support capabilities, but requires careful management of governance, ethics, and system complexity.

III. RESEARCH METHODOLOGY

This study adopts a qualitative research methodology to explore intelligent decision support systems for enterprise modernization using generative AI, predictive modeling, and process automation. A qualitative approach is selected because the research focuses on conceptual understanding, architectural analysis, and synthesis of interdisciplinary knowledge rather than quantitative measurement or experimental validation. Intelligent decision support systems represent a rapidly evolving domain where technologies, frameworks, and implementation practices are continuously changing, making interpretive analysis essential for meaningful insights.

The research is grounded in an interpretivist philosophical paradigm, which assumes that decision support systems, AI models, and enterprise processes are influenced by organizational context, technological infrastructure, and human interaction. This perspective allows the study to examine how enterprises adopt intelligent decision support systems based on their operational needs, digital maturity, and strategic goals. Rather than seeking universal principles, the study aims to develop a comprehensive understanding of how AI-driven decision systems operate within modern enterprises.

A descriptive and exploratory research design is employed to systematically analyze existing literature, frameworks, and industry practices related to decision support systems, generative AI, predictive modeling, and process automation.



The descriptive component focuses on documenting current technologies, system architectures, and analytical models, while the exploratory component investigates emerging trends such as autonomous decision intelligence, generative analytics, and hyperautomation frameworks.

The study relies entirely on secondary data sources, including peer-reviewed journal articles, conference proceedings, industry white papers, technical documentation, and reports from leading technology organizations. Academic databases such as IEEE Xplore, ACM Digital Library, ScienceDirect, SpringerLink, Scopus, Web of Science, and Google Scholar are used to collect relevant literature. Keywords include “intelligent decision support systems,” “generative AI in enterprise,” “predictive modeling frameworks,” “process automation in business,” “decision intelligence systems,” “machine learning forecasting,” “RPA enterprise automation,” and “AI-driven business analytics.”

A systematic literature review (SLR) methodology is applied to ensure structured identification, evaluation, and synthesis of relevant studies. The review process begins with defining research questions focused on how generative AI, predictive modeling, and process automation contribute to enterprise decision support systems. Inclusion criteria prioritize recent, high-impact, peer-reviewed studies relevant to AI-driven decision systems and enterprise modernization. Exclusion criteria eliminate outdated, non-peer-reviewed, or irrelevant sources lacking methodological rigor.

Key Capabilities Of An AI Decision Support System

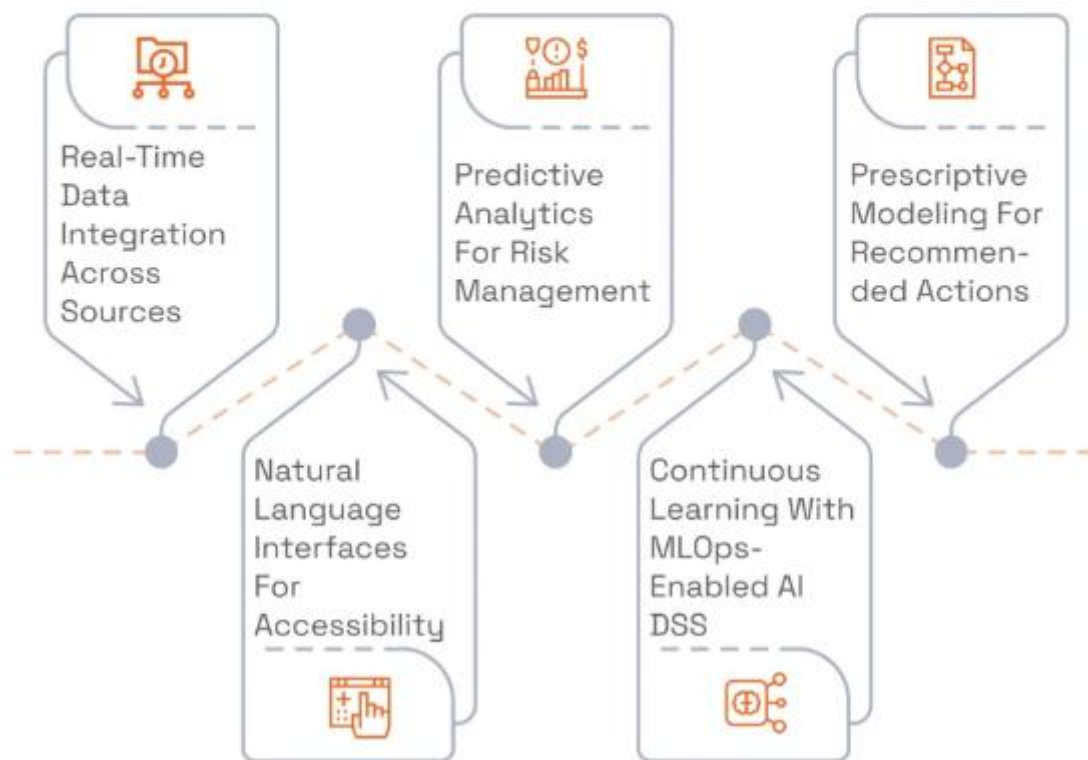


Fig.1.The Rise of the Artificial Intelligence Decision Support System



The selected literature is analyzed using thematic analysis, which involves coding and categorizing data into key conceptual themes. These themes include generative AI-based decision intelligence, predictive analytics systems, process automation frameworks, enterprise workflow optimization, machine learning applications in decision-making, AI governance, and digital transformation strategies. Each theme is examined to identify patterns, relationships, and differences across multiple studies.

Generative AI is analyzed in terms of its ability to generate insights, explanations, and scenario simulations for enterprise decision-making. The methodology examines how large language models and generative systems transform raw data into actionable intelligence. The role of prompt engineering, model fine-tuning, and contextual data integration is also explored.

Predictive modeling is evaluated through machine learning techniques such as regression, classification, clustering, and deep learning. The study investigates how predictive models enable forecasting of business outcomes, risk identification, and operational optimization. Data preprocessing, feature engineering, and model training processes are also analyzed.

Process automation is examined through robotic process automation, intelligent workflow orchestration, and hyperautomation frameworks. The methodology evaluates how automation systems execute decisions, streamline workflows, and reduce manual intervention. Integration with AI systems for adaptive automation is also studied.

To enhance validity and reliability, triangulation is employed by comparing findings across academic literature, industry reports, and technical documentation. This ensures that conclusions are supported by converging evidence rather than isolated perspectives. Cross-validation strengthens credibility in interpreting the role of AI in decision support systems.

Comparative analysis is conducted between traditional decision support systems and AI-driven intelligent systems. Traditional systems rely on static reporting and historical analysis, whereas modern systems incorporate generative AI, predictive modeling, and real-time automation. This comparison highlights significant improvements in speed, adaptability, and decision accuracy.

Ethical considerations are addressed by ensuring accurate representation of all sources, maintaining academic integrity, and avoiding misinterpretation of AI-related concepts. Since the study is based entirely on secondary data, no human participants or sensitive datasets are involved, minimizing ethical risks. However, careful attention is given to responsible interpretation of AI-driven decision-making systems.

The study acknowledges several limitations. The rapid evolution of AI technologies means that new models, frameworks, and methodologies may emerge beyond the scope of this research. Additionally, reliance on secondary data limits the ability to validate findings through real-world implementation or experimental evaluation. Despite these limitations, the methodology provides a strong conceptual foundation for understanding intelligent decision support systems.

Overall, this research methodology provides a structured and rigorous approach to analyzing how generative AI, predictive modeling, and process automation collectively drive enterprise modernization. Through systematic literature review, thematic analysis, triangulation, and comparative evaluation, the study generates comprehensive insights into the architectural, technological, and governance dimensions of intelligent decision systems in modern enterprises.

IV. RESULTS AND DISCUSSION

Intelligent Decision Support Systems (IDSS) are becoming a cornerstone of enterprise modernization, driven by the convergence of generative AI, predictive modeling, and process automation. These systems represent a significant evolution from traditional decision support tools, which were largely static, rule-based, and dependent on historical reporting. Modern IDSS architectures are dynamic, continuously learning, and capable of generating recommendations, simulating outcomes, and executing automated workflows across enterprise environments.

A key finding is that enterprise decision-making is shifting from human-centric analytical interpretation to AI-augmented and partially autonomous decision ecosystems. Cloud platforms such as Microsoft, Amazon Web Services, and Google provide foundational infrastructure for deploying intelligent decision systems at scale. These platforms



offer integrated services for generative AI model deployment, predictive analytics pipelines, and workflow automation, enabling organizations to operationalize intelligence directly within business processes.

Generative AI plays a transformative role in decision support by enabling systems to create insights, scenarios, and recommendations in natural language and structured formats. Unlike traditional machine learning models that only predict outcomes, generative models can simulate multiple future scenarios, explain potential risks, and propose actionable strategies. This capability enhances strategic planning, operational optimization, and customer engagement by providing decision-makers with richer contextual intelligence.

Predictive modeling remains a core component of intelligent decision support systems. Machine learning models analyze historical and real-time data to forecast demand, detect anomalies, and identify operational inefficiencies. Data platforms such as Snowflake and Databricks provide scalable environments for training and deploying predictive models using unified data architectures. These platforms enable continuous learning, allowing models to adapt to changing business conditions and improve decision accuracy over time.

Process automation is another critical pillar of intelligent decision support systems. Automation platforms such as ServiceNow and Salesforce enable enterprises to translate AI-driven insights into actionable workflows. ServiceNow automates IT operations, incident management, and enterprise workflows, while Salesforce enhances customer relationship management through intelligent lead scoring, personalized recommendations, and automated sales processes. This integration ensures that decisions generated by AI systems are executed efficiently across enterprise functions.

A significant architectural trend is the integration of decision intelligence into enterprise resource planning (ERP) and business process management systems. Platforms such as SAP and Oracle embed AI capabilities directly into core business functions, enabling real-time financial analysis, supply chain optimization, and human resource planning. This eliminates the separation between analytics and operations, making decision-making a continuous and embedded process.

Generative AI enhances enterprise modernization by enabling natural language interfaces for decision systems. Business users can interact with systems using conversational prompts to generate reports, analyze trends, and simulate outcomes. This reduces dependency on technical expertise and democratizes access to advanced analytics across organizational levels.

Another key finding is the rise of autonomous decision workflows powered by agentic AI systems. These systems combine predictive modeling, generative reasoning, and automation to independently execute decisions under defined constraints. For example, in supply chain management, AI agents can predict demand fluctuations, generate procurement strategies, and automatically execute orders while continuously monitoring outcomes.

Security, governance, and explainability remain critical challenges in intelligent decision support systems. As AI systems increasingly influence business-critical decisions, ensuring transparency and accountability becomes essential. Organizations must implement AI governance frameworks that include model explainability, audit trails, and compliance validation mechanisms.

Hybrid and multi-cloud environments also play a crucial role in enabling scalable decision systems. Platforms such as IBM, Alibaba Cloud, and container orchestration systems like Red Hat OpenShift support distributed deployment of decision intelligence workloads. These systems ensure scalability, resilience, and regulatory compliance across global operations.

Despite these advancements, challenges such as model drift, data inconsistency, and integration complexity remain significant barriers. Ensuring data quality and maintaining alignment between predictive models and real-world business conditions is essential for sustained performance.

Overall, intelligent decision support systems represent a major advancement in enterprise modernization, enabling organizations to transition from reactive decision-making to proactive, predictive, and autonomous intelligence-driven operations.



V. CONCLUSION

The study of intelligent decision support systems highlights a fundamental transformation in enterprise modernization strategies. The integration of generative AI, predictive modeling, and process automation enables organizations to enhance decision-making speed, accuracy, and scalability.

Generative AI enhances decision support by enabling scenario generation, natural language interaction, and automated insight creation. Predictive modeling provides the analytical foundation for forecasting and risk detection, while process automation ensures that insights are translated into executable actions across enterprise systems.

Platforms such as Snowflake and Databricks provide the data infrastructure necessary for scalable predictive analytics, while ServiceNow and Salesforce enable automation of enterprise workflows. ERP systems such as SAP and Oracle further integrate decision intelligence into core business processes.

Despite these advancements, challenges remain in ensuring transparency, data quality, and system interoperability. Organizations must implement robust governance frameworks to ensure that AI-driven decisions are explainable, reliable, and aligned with regulatory requirements.

Overall, intelligent decision support systems represent a critical enabler of enterprise modernization, allowing organizations to operate with greater agility, intelligence, and automation.

VI. FUTURE WORK

Future research in intelligent decision support systems should focus on improving autonomy, explainability, and interoperability across AI-driven enterprise environments. One key direction is the development of fully autonomous decision systems capable of generating, evaluating, and executing decisions with minimal human intervention.

Another important area is the enhancement of explainable AI techniques to ensure that generative and predictive models provide transparent reasoning for their outputs. This is particularly important in regulated industries such as finance, healthcare, and government.

Integration of real-time data from IoT devices and edge computing systems will further enhance decision accuracy and responsiveness. This will enable enterprises to make decisions based on live operational conditions rather than historical data alone.

Improving interoperability between different AI systems and enterprise platforms is also critical. Standardized APIs and data exchange protocols will enable seamless integration across multi-vendor ecosystems.

Finally, future systems must address ethical concerns such as bias, fairness, and accountability in AI-driven decision-making. Robust governance frameworks will be required to ensure responsible deployment of intelligent decision support systems.

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