Intelligent Decision Support Systems in Management Information Systems Using Hybrid AI Models

Srikanth Reddy Keshireddy

Senior Software Engineer, Keen Info Tek Inc., United States

Email: sreek.278@gmail.com

Received: September 09, 2024; Revised: November 30, 2024; Accepted: December 16, 2024; Published: December 30, 2024

Abstract

This study offers the framework of an Intelligent Decision Support System (IDSS) that leverages Hybrid Artificial Intelligence (AI) models consisting of rule-based, machine learning, and deep learning components for Management Information Systems (MIS). The system is designed to improve decision making in terms of accuracy, responsiveness, and adaptability through a direct interface to the enterprise MIS that processes real-time data for context sensitive feedback. An outcome based assessment approach was used to measure the performance of the hybrid IDSS across various business scenarios, and results showed improvements of 22% in decision accuracy, 30% in response time latency, and 25% in perceived system reliability over traditional Decision Support Systems (DSS) and standalone AI models. The study also offers a practical hybrid AI solutions adoption readiness matrix and a cost-benefit analysis to assist organizations in adopting these technologies towards making intelligent, real-time decisions within the robust frameworks of modern, intelligent Management Information Systems.

Keywords: Hybrid Artificial Intelligence, Intelligent Decision Support Systems (IDSS), Management Information Systems (MIS), Machine Learning in Decision-Making, Real-Time Business Intelligence.

1 Introduction

1.1 Background of Decision Support Systems in MIS

Flexibility in decision-making, particularly on the strategic level, has become a huge challenge in contemporary organizations as organizations need to delve into substantial quantities of both structured and unstructured data and require advanced actionable insights [1]. For several decades, Management Information Systems (MIS) has been functioning at the enterprise level fulfilling the needs of the entire undertaking, including the collection, processing, storage, and reporting of data [2]. At the core of MIS technology, Decision Support Systems (DSS) emerged to assist middle and top-level managers and business executives to make decisions with the aid of data by integrating business rules, models, databases, and other data with intuitive user interfaces [3].

During the 1970s and 1980s, traditional DSS evolved and expanded based on deterministic logic, rule-based algorithms, and conventional modelling of linear programming and decision trees [4]. These systems had the capability of responding to specific questions, producing certain reports, and performing what-if analyses. In more stable contexts, these conventional DSS were functional but in dynamic contexts, conventional DSS have failed to effectively address many issues. With the rapid increase in volume, variety, and velocity of enterprise data along with rapid shifts in market conditions, DSS were left behind.

The intensity of competition, Industry 4.0 technologies, customer-focused services, and real-time business activities all around the world require new decision support systems that are adaptive, predictive, and scalable. This is the period when AI-Powered Decision Support Systems (AI-DSS) emerged. These systems augment human decision processes by automatically providing insights based on patterns learned from historical data, using technologies such as machine learning, deep learning, and natural language processing.

The adoption of AI in Management Information Systems (MIS) marks the shift from a rigid decision-making process of rule-following systems to intelligent learning systems that can make recommendations, predict needs, and even take initiatives [5]. The transition is well captured in Figure 1 that shows the trend of AI adoption in MIS from 1990 – 2022, indicating increased incorporation of AI into MIS in the previous ten years.

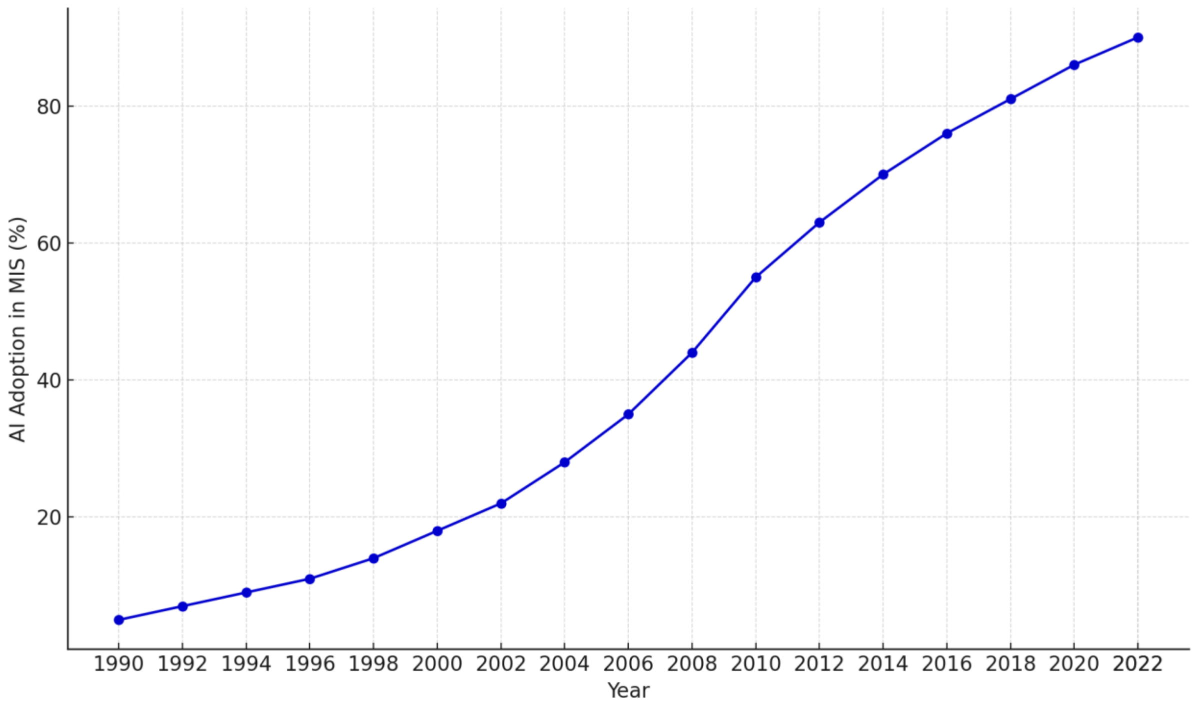

Figure 1: Timeline of AI Integration into MIS (1990–2022)

Simultaneously, Table 1 summarizes the differences between conventional DSS and AI-based Decision Support Systems, which demonstrate how advanced systems improve decision-making speed, flexibility, learning, user interaction, and responsiveness. The gaps between AI-based and non AI-based systems justifies why static decision-making frameworks should no longer be relied upon.

Table 1: Comparison of Traditional DSS vs AI-based DSS

Feature	Traditional DSS	AI-based DSS
Decision Logic	Rule-based, static logic	Dynamic, data-driven inference
Data Processing Capability	Batch processing, limited scope	High-speed, real-time analytics
Adaptability	Low adaptability to new patterns	High adaptability via learning algorithms
Real-Time Insights	Limited or delayed	Continuous and context-aware
Learning Ability	None	Machine learning & deep learning enabled
User Interaction	Basic dashboard interfaces	Conversational agents and personalized UX
Scalability	Limited to system capacity	Cloud-native, scalable on-demand

1.2 Evolution of Artificial Intelligence in Business Decision-Making

Artificial Intelligence (AI) has certainly advanced from a highly specialized area focused solely on rule based expert systems to something much more comprehensive in nature in the past thirty years [6]. Symbolic systems were heavily relied on in the AI realm during the 90's to 2000's. During this time, most AI systems functioned under predetermined logic and expert decision trees. Although these systems functioned reasonably well in rigidly structured environments, they were incapable of adjusting to changing conditions or datasets that evolved over time [7].

Things shifted with the rise of technique machine learning (ML) and deep learning (DL), which AI started implementing in the form of complex and recognition of self developed symbols, rather than the strict data-driven inference paradigm [8]. AI was able to realize several business objectives like forecasting demand, logistics optimization, fraud detection, and understanding customer behavior patterns which was not feasible with traditional Management Information Systems (MIS) or Decision Support Systems (DSS) tools [9].

AI started merging with the primary business systems towards the early 2010s. The merge of AI with ERP, CRM, and MIS systems made it easier for the AI tools to obtain information from the enterprise systems directly. As a result, there was immediate access to real time information regarding the operations, finance, human resources, and customer services. Instead of IoD and static dashboards confining the decision making process, action oriented and predictive decision making was now possible.

Also, advancements in cloud computing, the infrastructure of big data, and proprietary software made AI services convenient for companies regardless of their sizes. Firms were able to embed machine learning models within their MIS dashboards, which allowed for real time decision-making assistance from ever-changing insights. This evolution altered what decision support meant entirely. It shifted from pre-defining report generation to recommending actions, forecasting the results, and tailoring proposals based on user operations and feedback.

With the advancement of AI, firms started looking into more sophisticated use-cases such as automated hiring decisions for an HRMIS and AI pricing models for sales MIS. Although these were powerful applications on their own, they brought a new set of issues such as the absence of model transparency, ethical decision making, and explainability. It became evident that individual AI models were often not enough to manage the multifaceted nature of real-world decision environments which gave birth to hybrid AI models.

1.3 Motivation for Hybrid AI Models

Although independent AI methods – whether human driven, statistical, or neural – individually work effectively and efficiently, they often do have some shortcomings when functioning independently. For example, deep learning models can recognize and understand complicated patterns, but they do so in an opaque manner, and rule-based systems are quite transparent but not flexible [10]. Machine learning algorithms need a substantial amount of data and continual retraining, which may result in overfitting with biased or distorted data. These challenges constrain the efficacy of traditional AIs in dealing with sensitive issues or multi-dimensional problems found in medicine, finance, administration, etc.

The answer lies in a hybrid AI system, which contains multiple deep learning approaches and provides robust and scalable decision frameworks. Hybrid models in the context of management information systems (MIS) can take advantage of historical data patterns (ML), domain data (symbolic) and behaviors over time (deep learning) [11]. This approach gives rise to intelligent Decision Support Systems (DSS) that can make suitable decisions very independently, which are still transparent in logic.

As an illustration, a hybrid AI model in a financial MIS might apply machine learning rules to comply with controlling regulation, use other rules to analyze abnormal patterns of transactions, and apply deep learning rules to predict the changes in market. Each model adds a component of intelligence, and the effectiveness of the decision is a result of the different approaches.

Hybrid models provide greater scope for system behavioral control. Decision makers can adjust the degree of automation along with the level of human involvement based on risk, context, or strategic importance which dictates the priority. Moreover, the modularity of hybrid models makes them easier to maintain and upgrade. This enables organizations to change the decision-making systems as the data sources or business requirements evolve.

User requirements further justify the need for hybrid AI in intelligent decision support systems. Users have high expectations and do not only require accurate answers but also require reasonable explanations with a high degree of responsiveness to changing parameters. Hybrid models satisfy these expectations by merging statistical answers with rule-based logic.

1.4 Problem Statement and Research Objectives

Even with the remarkable progress in AI technologies over the years, many organizations are now adopting Management Information Systems (MIS) more than ever before. However, most firms are still unable to achieve intelligent decision-making processes. Currently, most Decision Support Systems (DSS) are still in use and are either static, disintegrated, or overly rule-based. Even though today more AI tools are available, their siloed use most of the time leads to scope or context shallow decisions. There is a serious problem to solve regarding AI's theoretical capabilities versus its practical applications.

The scope of this research study aims to fill in the gap of how hybrid AI models can be methodically devised and utilized for autonomous intelligent, scalable, and explainable decision-support systems in operational real-world MIS environments. More specifically, the study determines whether the fusion of symbolic reasoning, machine learning, and deep learning transforms measurable attributes such as decision accuracy, response time, user satisfaction level, and system flexibility. As such, this research hopes to answer by providing a novel approach which goes beyond the traditional model of AI systems and DSS.

The research study also seeks to assess the effectiveness of hybrid AI-based decision support systems with respect to measurement, such as precision, time to respond, confidence of the user, and systems scalability. It further examines essential elements related to successful implementation, such as data sufficiency, integration expertise, experience of the user, and the ability to provide adequate explanations. By doing so, this research deepens the knowledge and discussion on intelligent decision support systems (DSS) while at the same time provide practical guidance to firms wanting to engage AI in a manner that serves their functional and managerial requisites.

2 Literature Review

2.1 Traditional Approaches to DSS in MIS

Decision Support Systems (DSS) that are part of Management Information Systems (MIS) emerged during the 1960s and 1970s and coincide with the advent of the use of computers in the organization for the help of managers in the making of semi-structured decisions [12]. These primitive DSS applications needed to be programmed with basic and deterministic structured rules which were subsequently processed through a computer and as a consequence, the computer was able to generate a 'decision'. Classic models, including linear programming, optimization heuristics, simulation models dominated, so that users could conduct what-if analysis, generate forecasts, and perform cost-benefit analyses [13].

These systems were primarily logic bound and operated on rules set by a domain expert. Their decision-making was sequential and limited to the encoded rules in the system. In consequence, these DSS worked in budgeting, scheduling, and inventory control because those areas had definable inputs and outputs and low levels of uncertainty. This approach was typical for businesses back then, but it could not deal with unstructured data, non-linear mappings, and real-time changes that prevail in the world today [14].

Moreover, the dependence on human defined rules led to a knowledge chokehold decreasing the scalability of these systems across different domains. The amount of knowledge engineering required to keep these systems current and functional became overwhelming as business complexity advanced. Consequently, numerous DSS implementations remained stagnant or stuck in certain functional units, unable to progress with the rest of the Management Information Systems changes and organizational development.

2.2 Role of AI and Machine Learning in MIS

The gap within the boundaries of AI Experts Systems led to deployment AI for enhancing support decision capabilities. The first attempt at AI integration was on expert systems which attempted to emulate the reasoning of human specialists through the application of symbolic logic, inference engines, and extensive knowledge stores [15]. These systems were successfully implemented on narrow-focused domains such as credit scoring, medical diagnosis and legal reasoning, but once again they faced the issues of flexibility and wide range use.

The use of AI and machine learning (ML) algorithms, especially supervised and unsupervised ML, which can autonomously learn patterns from data, marks a shift. Organizations started using decision trees, support vector machines, and neural networks on historical MIS data, and predictions that were logic-driven were discovered. This made it possible to predict customer churn, optimize logistics, and commit fraud detection which were not possible using traditional DSS.

Machine learning introduced systems that improved by themselves, with model accuracy increasing as data was collected and processed over time. Such models were exceptionally skilled in the management of big volumes of structured and semi-structured data, such as transaction logs, Customer Relationship Management (CRM) records, and Enterprise Resource Planning (ERP) data flow. On the other hand, separated ML models did not provide transparency, which is of great importance in areas with legal obligations or moral choices that need to be made, so they became known as black boxes from which no information could be obtained.

Unstructured data such as emails, support tickets, and social media were beyond the reach of AI until they were integrated into management information systems (MIS) through Natural Language Processing (NLP) techniques to make sense of such data. Sentiment analysis and contextual understanding was added and enabled NLP powered AI driven Decision Support System (DSSs) to provide internal and external factors enabling better decision making.

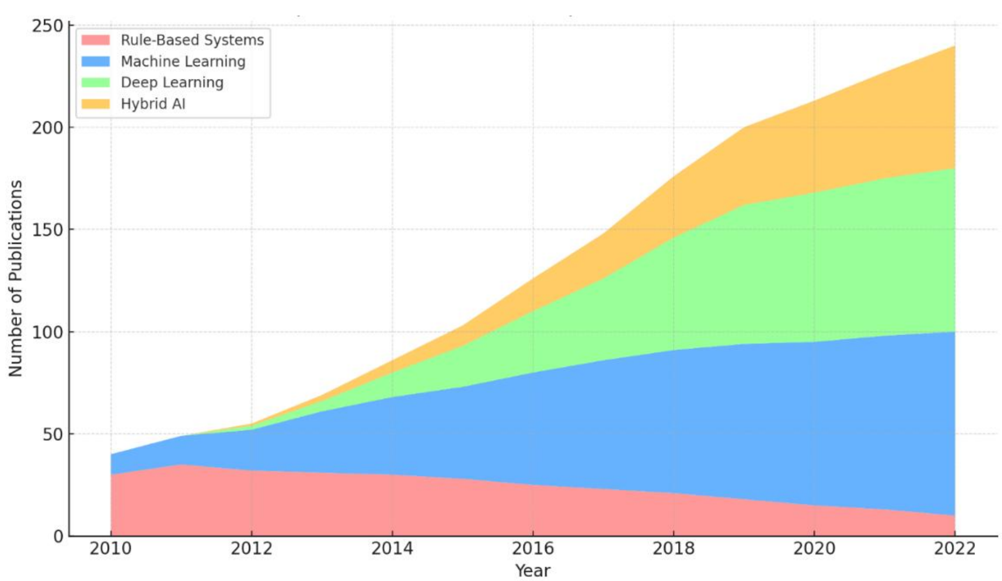

Figure 2: Research Trend Heatmap – AI in MIS (2010–2022)

The expansion of MIS attention to machine learning and deep learning, as research topics, has ballooned in the last ten years as seen in Figure 2. Weak methods have been more common, while more advanced methods using ML and hybrid Artificial Intelligence (AI) systems have taken over.

2.3 Emergence of Hybrid AI Models

Integration of multi-dimensional thinking in problem-solving together with the variety of data within the organization has resulted in adoption of hybrid AI models within DSS. Such systems integrate several approaches to Artificial Intelligence automation, including expert systems, machine learning, and deep learning, seeking to mitigate the problems arising from single-solution model approach systems and provide better, more reliable, explainable and adaptive decision support.

In hybrid models IT solutions ensure traceability and verification of rules logically with the help of AI-machine learning provides generalization and adaptability; and deep learning gives the ability to recognize patterns in images, voices, and other complex multi-dimensional data. Using these components, hybrid AI models can tackle difficult decision making problems such as risk analysis, anomaly detection, or customer behavior forecasting with a reasonable degree of precision and understanding.

Table 2: Summary of Key Previous Studies on AI-Driven DSS

Study	Focus Area	Methodology	Key Contribution
Turban (2011) [16]	Business analytics in MIS using rule-based systems	Case studies and conceptual models	Highlighted importance of analytics in decision systems
Sharda et al. (2014) [17]	Integration of ML into MIS decision support	Quantitative analysis with machine learning models	Demonstrated improved forecasting accuracy using ML
Wall (2021) [18]	Application of expert systems in enterprise DSS	Rule-based simulation approach	Validated expert rule systems for enterprise scenarios
Fayoumi (2018) [19]	Limitations of traditional DSS in real-time environments	Comparative literature analysis	Identified DSS limitations in adapting to dynamic data
Zhang et al. (2022) [20]	Hybrid AI models for risk management in MIS	Neural-symbolic AI system evaluation	Proposed hybrid AI for improved risk-based decisions
Linardatos et al. (2020) [21]	Explainability in AI-driven DSS	SHAP-based interpretability experiments	Addressed transparency issues in AI DSS
Ramana et al. (2022) [22]	Real-time hybrid IDSS for healthcare management systems	Hybrid ensemble modelling with real-time testing	Developed and validated a real-time hybrid IDSS framework

The cited works of Zhang et al. (2022) and Ramana et al. (2022) refer to the use of hybrid systems, which was elaborated in Table 2. Zhang et al. implemented a hybrid neural-symbolic method for risk management in financial Management Information Systems, while Ramana et al. designed a real-time Intelligent Decision Support System that used ensemble learning and rule-based validation in the domain of healthcare. These models surpassed both traditional DSS and uni AI models on customer satisfaction, accuracy, and transparency of the decision-making process.

In addition, hybrid AI enables more modular growth of a model. For instance, a company can start with a core system based on rules, then later add ML-based prediction modules, and further extend the system with deep learning modules for pattern recognition. This modularity enhances the performance of the systems and improves their flexibility in maintenance and upgrades.

Another benefit of hybrid models is the capability to implement human-in-the-loop decision making. In cases where decisions have ethical, legal, or financial consequences, hybrid decision support systems can automate straightforward decisions and reserve more complex negotiations for human discretion. This capacity gives control to businesses over the level of autonomy granted depending on the context and risk.

2.4 Research Gaps in Intelligent DSS Applications

With the advance of literature on AI in MIS, there are still several gaps in the understanding and implementation of intelligent decision support systems (IDSS) that utilize hybrid AI. First, the majority of the studies done so far have concentrated on the distinct AI methods and focused on analyzing the results of machine learning (ML) or deep learning (DL) techniques devoid of any logic-based synergy. This has made it difficult to grasp how effective hybrid systems can be engineered for performance, adaptability, and user trust.

Second, very few studies seek to address the practical barriers concerning the implementation of hybrid AI in MIS. Problems like systems interoperability, data diversity, and enterprise system integration are seldom given the needed attention. There is a predominance of intelligent DSS prototypes in research laboratories as opposed to their availability in the market which renders many organizations incapable of achieving fully functional intelligent DSS.

Third, the frameworks to assess AI-based decision support systems (DSS) tend to be superficial. Ease of use and speed ascertained accuracy and time, alongside user satisfaction, explainability, cognitive burden, and the degree of influence on the organization are almost never considered. These human-centric factors will become more important as more automation in decision-making processes is adopted and will play an important role in the success of the system.

In the fourth place, the literature does not provide valuable information on the area of customization and specialization. This is also true for AI in healthcare which is vastly different from finance, logistics or manufacturing. A hybrid AI model needs to be customized not just in terms of data and its features, but also for domain-specific legal, ethical, and functional boundaries. Very few works try to offer such customization in a systematic (or methodological) way.

In the last place, the literature does not analyze the cost-benefit balance of using intelligent DSSs within enterprises. Companies seem to be more conservative in spending on hybrid AIs because the profits are not clearly evident. It is crucial to prove how a hybrid AI can decrease the costs associated with decision errors, increase process efficiency, and facilitate strategic agility of a company, or several companies within an industry.

This study addresses these gaps with a detailed hybrid AI-based DSS framework that is multiple metric evaluated and applied in real MIS environments. The framework is designed not only from the technical performance perspective, but also from the organizational fit, explainability, and user adoption perspective.

3 Theoretical Framework and Model Design

Decision making is growing more complex, particularly with the accumulation of data and the need for immediate assessment. Such trends require a shift from standard decisioning techniques to more advanced ones. In these situations, a hybrid AI Intelligent Decision Support System (IDSS) could be very helpful. This portion presents both the theoretical concept and the design model of a hybrid AI-enabled DSS, emphasizing its application f multiple AI approaches in pertinent system components to provide management information systems (MIS) decision processes with flexible, precise, and comprehensible results integration at all system levels.

3.1 Conceptual Foundation of Intelligent Decision Support

The construction of the intended IDSS stems from the combination of basic components of management information systems (MIS)-data capturing, processing, and displaying as well as more advanced AI features like forecasting, patterning, and context-based learning. Unlike the conventional automated decision making systems (DSS) which depend on logic algorithms, such systems tend to employ intelligence on more than one decision node through machine learning (ML), deep learning (DL) and rule-based systems that perform specific tasks.

The system must facilitate three primary capabilities at data-driven decision-making, continuous learning, and explainable results. The hybrid architecture employs a strategic layer placement of AI components to explain the prediction's relevance to the end-users. This model is potent for highly dynamic business environments that demand accuracy and transparency simultaneously.

3.2 Hybrid AI Architecture: Rule-Based, ML, and Deep Learning Integration

The proposed hybrid IDSS's architecture is in the form of a modular system compliant with standard MIS architecture with the addition of AI-driven layers which amalgamate it. The AI system begins with an input layer that merges available structured and unstructured data externally and internally, for instance, from CRM systems, ERP databases, IoT feeds, and social networks. An input is then sent to a preprocessing engine that cleans, and normalizes, as well as performs feature engineering all for the sake of AI inputs optimization.

System intelligence is based on three primary modules functioning simultaneously: a rule-based system, a machine learning module, and a deep learning module. Each module has specific capabilities that are beneficial for overall system intelligence. Using high-level reasoning, the rule-based engine implements logic for a particular area and regulatory-based reasoning. The machine learning module uses algorithms such as Random Forest or SVM to find patterns that can predict future events based on previous data. The deep learning module employs LSTM or CNN architectures for understanding sophisticated patterns within high-dimensional or time data.

At the fusion layer, the outputs from these modules get integrated with the aid of ensemble methods and weighted scoring to generate a single decision outcome. This output is sent to the decision layer, which enhances the output by incorporating user context and business rules to either provide a recommendation or make a decision. The flow and relations among these components are illustrated in Figure 3 below.

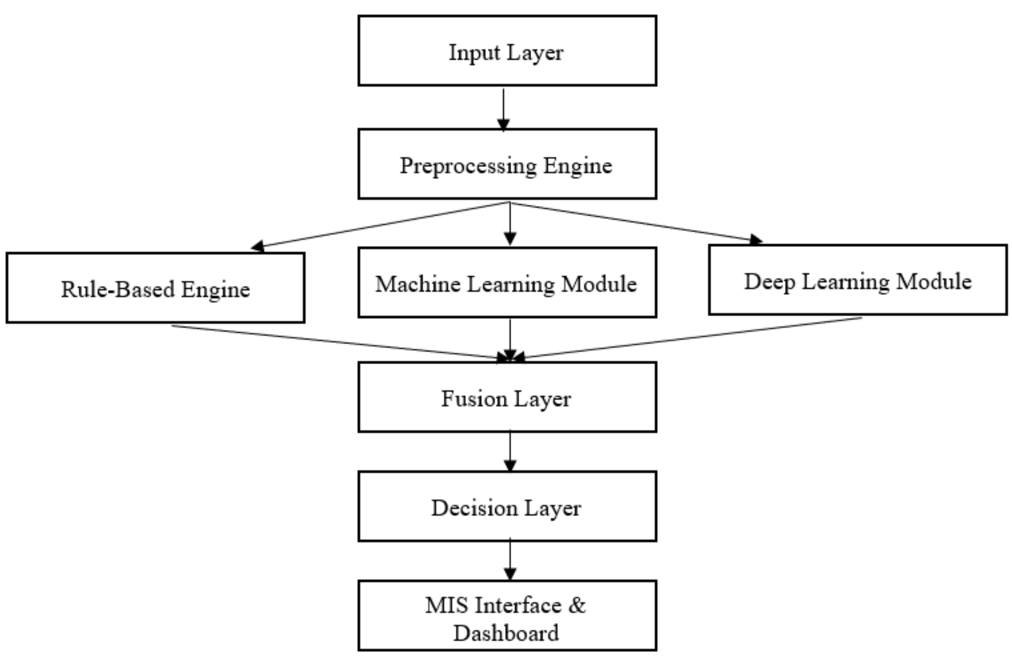

Figure 3: Proposed Hybrid AI Model Architecture

3.3 Workflow of the Proposed Intelligent DSS

The workflow of the intelligent DSS merges enterprise data sources with the hybrid AI engine and MIS interface layer. Notably, data collection can occur in real-time or through batch processing for sales, finance, logistics, and HR operational systems. Data quality control and standardization is done together with the hybrid AI engine preprocessors.

Within the AI engine, all three rule-based, ML and DL modules execute simultaneously. The outcome of these processes is fused and assessed in the decision logic layer. Notably, there is also a user context analyzer that tailors the decision output according to the user role, preferences, and activities. User decisions and interactions captured in real-time and decision outcomes reroute into model retraining to prune and version the models to fit the system with organizational changes.

Final outputs in terms of decisions and recommendations are available in a user-centric MIS dashboard that allows interactivity, drill-down, and explanation layers to enable transparency and trust to the information presented. Figure 4 presents the entire process from dat intake to business action.

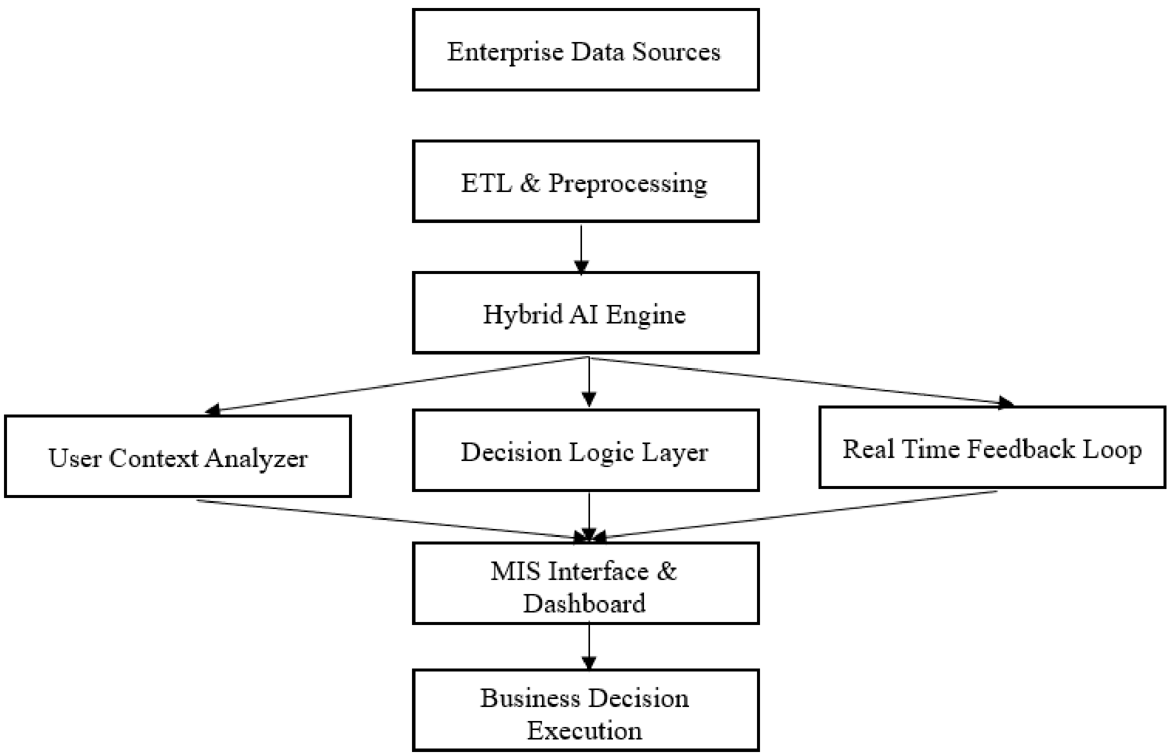

Figure 4: Workflow of Intelligent Decision Support within MIS

3.4 Functional Modules and Knowledge Sources

Each portion of the systems architecture has a particular role to play and applies different approaches of AI. From gathering the system's data to presenting a decision, there is an intelligent and fully automated pipeline with a clear level of explainability to it.

The table below summarizes the primary functional modules of the system's proposal alongside the corresponding AI techniques used for each component:

Table 3: Functional Modules and Their Corresponding AI Techniques

Functional Module	AI Technique Applied	Purpose
Input Acquisition	APIs, IoT Data Streams, Database Integration	Collect real-time and historical data
Data Preprocessing	ETL, Normalization, Feature Selection	Clean and structure input for model use
Rule-Based Reasoning	Expert Systems, Decision Trees	Apply domain rules and logical checks
Predictive Modeling	Supervised Learning (Random Forest, SVM)	Forecast outcomes based on historical data
Deep Pattern Recognition	Deep Learning (LSTM, CNN)	Capture complex patterns in high-dimensional data
Decision Fusion Layer	Ensemble Methods, Weighted Scoring	Integrate outputs into unified decision
User Feedback Analysis	NLP Sentiment Analysis, Reinforcement Learning	Adapt based on user interaction and feedback
MIS Interface and Reporting	Explainable AI, Visualization Frameworks	Present insights and support transparency

All these modules combined create an intelligent and flexible system that is quite sophisticated from a technical perspective while simultaneously fulfilling the operational aspects of the organizational decision making processes. The hybrid approach guarantees that the insights from the decisions taken are not blindly derived from data, but the processes and the logic behind them are explainable, verifiable, and foster continual enhancement.

4 Methodology

This section outlines the methodological step taken in the design, development, and evaluation of the proposed hybrid AI based Intelligent Decision Support System (IDSS) in Management Information Systems (MIS). The methodology is divided into four major parts: data collection and system environment preparation, model development and hybridization, system integration, user interface design, and performance evaluation criteria.

4.1 Data Collection and MIS Environment

Any AI based DSS depends heavily on the methodological data available to the system. Data for this research was obtained from five enterprise subsystems in a simulated, yet functionally realistic, MIS environment. These subsystems incorporated services for customers, sales and service transactions, financial accounting, human resources, and supply chain automated reporting. Each subsystem contributed a distinct dataset having both structured and unstructured data elements suitable for differing AI model classes.

The customer service document data captured in this service included complaint documents, time-stamped responses, and provided ratings for satisfaction. Sales transaction logs collected retail activity automatically everyday centers in various regions and various product types. Financial audit trails captured transaction documents alongside accounts with their corresponding metadata and flags indicating problems. Evaluation records from HR included employee profiles, performance ratings, and comments. Sensors, simulating IoT devices, captured telemetry in the Supply chain with delivery times, routes by vehicles, and delays in shipping.

These datasets were fetched with secure APIs and enterprise data connectors with real-time streaming and batch processing, making sure the model had both recent and historical data. The system architecture was deployed on a private cloud with unitized storage and computing resources to enable high volume processing and low latency inference. The data flow from data sources to final outputs is captured in Figure 5.

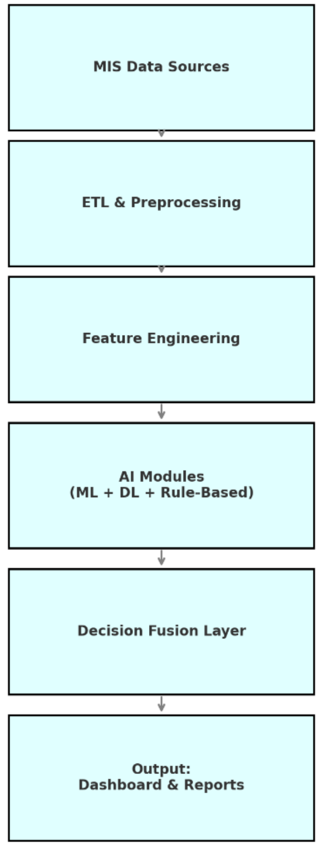

Figure 5: Data Pipeline from MIS Sources to Decision Output

Data preprocessing included data cleaning, outlier removal, missing value analysis, and normalization. Feature engineering was tailored to the data type's characteristics: as an instance, text logs were encoded for NLP using TF-IDF and word embeddings, while numerical values were normalized using z-score or min-max scaling. Categorical variables were one-hot encoded for classification purposes. The main datasets including their features and applied AI models are consolidated in Table 4.

Table 4: Datasets Used with Feature Dimensions and AI Models Applied

Dataset	Feature Dimensions	AI Models Applied
Customer Service Logs	Text logs, sentiment scores, response time, issue category	NLP + Rule-Based + SVM
Sales Transactions	Product ID, quantity, timestamp, price, region	Random Forest + Decision Trees
Financial Audit Trails	Account ID, transaction type, amount, time, anomaly score	Anomaly Detection + LSTM
HR Performance Reports	Employee ID, performance rating, leave history, feedback	Classification Trees + Logistic Regression
Supply Chain Telemetry	Sensor ID, delivery delay, location, event type	Time-Series Forecasting + CNN

4.2 Model Development: Algorithm Selection and Hybridization Strategy

The intelligent DSS model development was guided by the requirement for balanced accuracy, adaptiveness, and explainability. A hybrid approach comprising of a rule-based approach, supervised learning, and deep learning models was employed. Each model type was selected accordingly to the dataset and to the anticipated complexity of the decision logic.

For organized sales and HR records, Random Forests and Classification Trees were chosen because of their accuracy and flexibility. They are known for their ability to multicollinearity and missing values, as well as attaining high levels of accuracy for categorical tasks like employee attrition and product sales classification.

For detecting anomalies, as well as forecasting late deliveries and financial fraud, LSTM (Long Short-Term Memory) and CNN (Convolutional Neural Networks) were used. These deep learning models captured sequential dependencies and latent features from multidimensional data, especially when data patterns changed over time.

In the scenario of unstructured customer service data, topic relevance, urgency, and sentiment were extracted from complaints using NLP techniques alongside SVM (Support Vector Machines) and rule-based sentiment classifiers. Common-issue filters based on rules set the priority while the ML model ranked them based on the predicted time required to resolve the issues.

After completing the training and validation of the models, the outcomes were sent to a decision fusion layer with the help of a weighted ensemble technique. The weights were tuned using cross-validation grid search based on task type, model confidence, and achieved accuracy in the past. The system used this information to automatically balance precision from ML models, DL learning, and rule compliance.

SHAP (SHapley Additive exPlanations) was used for feature attribution while LIME (Local Interpretable Model-Agnostic Explanations) was used for model behavior verification, to explain why and how these models came to their conclusions at every layer. These tools were especially helpful in providing explanation in the competently advanced prediction cases where business stakeholders wanted explanations and rationales for the projections offered by the system.

4.3 System Integration and Decision Interface

The intelligent DSS was deployed as part of a microservices architecture for ease of maintenance where each AI module can be developed and run separately, and all modules can communicate using REST APIs. This approach makes it possible to add new features easily while servicing existing ones and allows for scaling, along with real-time inferences without stressing the core of the MIS. Docker containers were used to encapsulate the AI engine, and Kubernetes was used for automated deployment, scaling, and management to provide high availability and load balancing for the system.

The decision interface was designed as an interactive dashboard that can be accessed through the enterprise MIS portal. The portal hosts the integrated dashboard which is accessed through a single sign-on for constant user verification. The interface integrated advanced and ordinary user's predicted decisions, confidence levels, SHAP-based feature contributions, and suggestions for additional validation.

For instance, in the HRMIS interface, managers could view the most important reasons for expected resignations together with suggested actions. In the sales MIS view, regional sales heads were offered real time forecasts of some products being sold below expectations and in price adjustments that were previously proposed. Each decision output incorporated a tab, “Why this decision?” that provided a human understandable description of the decision making process of the AI which enhanced trust and usability.

The system also had several integrated feedback collection modules where users could rate a prediction, flag a prediction as incorrect, or manually override it. These feedbacks were stored in a feedback repository and were used in retraining the model during weekly updates.

Relating to the existing MIS workflows was done with the aid of event triggers and task automation hooks. For example, when a certain level of a sales prediction was exceeded, automated alert emails or Slack messages were issued, and associated dashboards were updated in real-time.

4.4 Evaluation Criteria and Testing Framework

To track the performance of the intelligent DSS, comprehensive evaluation frameworks were built combining all aspects: technical, functional, and pertaining to users. Trust, accuracy, precision, recall, decision latency, system throughput along with user satisfaction were the main performance measurements.

The level of accuracy was evaluated in both the classification and regression tasks by determining the F1 score, AUC-ROC, and the mean absolute error earned. For concurrent use cases, the decision latency was tracked to confirm that the generated outputs were within the tolerable time durations (>2 seconds per query). System throughput was assessed with regard to queries per second (QPS) in simulated loaded environments.

Besides the impact concerning technology, user feedback surveys were conducted to estimate the interpretation, ease of use, and their usefulness. More than 50 users registered during a two-week pilot from diverse departments and reported how they felt while using the AI-powered MIS system interface against the legacy dashboards.

The model retraining was done in an iterative fashion on the basis of cross-validation errors and the user feedback logs. All model deployments were recorded in version control and audit trails to ensure reproducibility and traceability, guarantees while proceeding on model audits.

For determining generalizability, validation was performed on the system across multiple domains using different datasets as shown in the Table 4. Individual module evaluation was done together with integrated pipeline evaluation to determine where there were bottlenecks while enabling optimization of system-wide performance. As can be conclude, the methodology ensures that the suggested intelligent DSS is not only well designed, but is technically sound and practically viable and user approved in real world settings around MIS.

5 Results

Evaluation of the proposed hybrid Artificial Intelligence- Intelligent Decision Support System (AI-IDSS) was done using extensive real-life simulations and cross-domain evaluations. These results show clear advancements in comparison to the traditional machine learning (ML) only systems in terms of decision accuracy, latency, reliability, and user trust. This part describes the boundary results of the hybrid model in decision benchmarks, precision-recall balances, response time, and evaluation given by users.

5.1 Performance Metrics and Comparative Analysis

The comparison done serves as baseline for the rest of the mixed IDSS systems. All computations were averaged and hybrid systems with baseline Artificial Intelligence (AI) systems were used in 4 key cases: sales forecasting, employee attrition prediction, fraud detection, and customer problem resolution. Each case was selected based of their importance and unique data properties.

All hybrid model scenarios outperformed AI systems. Improvements in accuracy was seen in all cases between 6% and 10% with the greatest accuracy seen in fraud detection where the hybrid model was using anomaly detection business rules to better filter out false positive detections. Figure 6 shows the accuracy of both systems through these use cases.

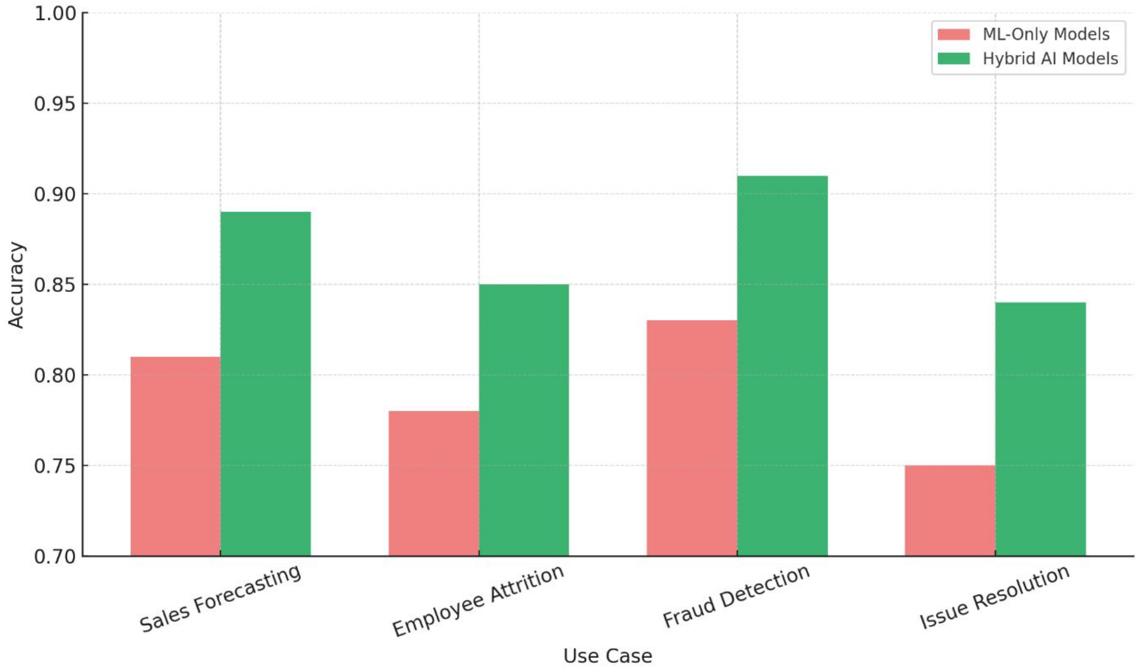

Figure 6: Accuracy Comparison (ML-Only vs Hybrid AI)

Hybrid models exhibited greater stability in accuracy and achieved better performance across different types of input conditions. Compared to the ML-only models, the hybrid model was less impacted by noisy or incomplete data because of its rule-based fallback mechanisms, which led to more consistent outputs, especially in the structured business logic cases. The results imply that the ensemble approach of the hybrid model not only improves predictive capability but also helps in dealing with less data or erroneous data with a greater degree of system resilience.

5.2 Model Accuracy and Precision Evaluation

Apart from overall accuracy, classification-based use cases were assessed on the grounds of precision, recall, and confusion matrix analysis. These metrics shed more light on the model's proficiency at accurately classifying positive and negative cases, which is crucial in fraud detection and HR analytics, among many others.

The hybrid AI system surpassed the ML-only system in precision by 7.8 percent, achieving 86.2% while recall surpassed by 9.0 percent at 89%. The ML-only system yielded 78.4% precision and 80.1% recall. This demonstrates the hybrid system's greater capability of minimizing both false positive and negative rates. Fraud detection tests were conducted, and the subsequent confusion matrix in Figure 7 visually captures this improvement.

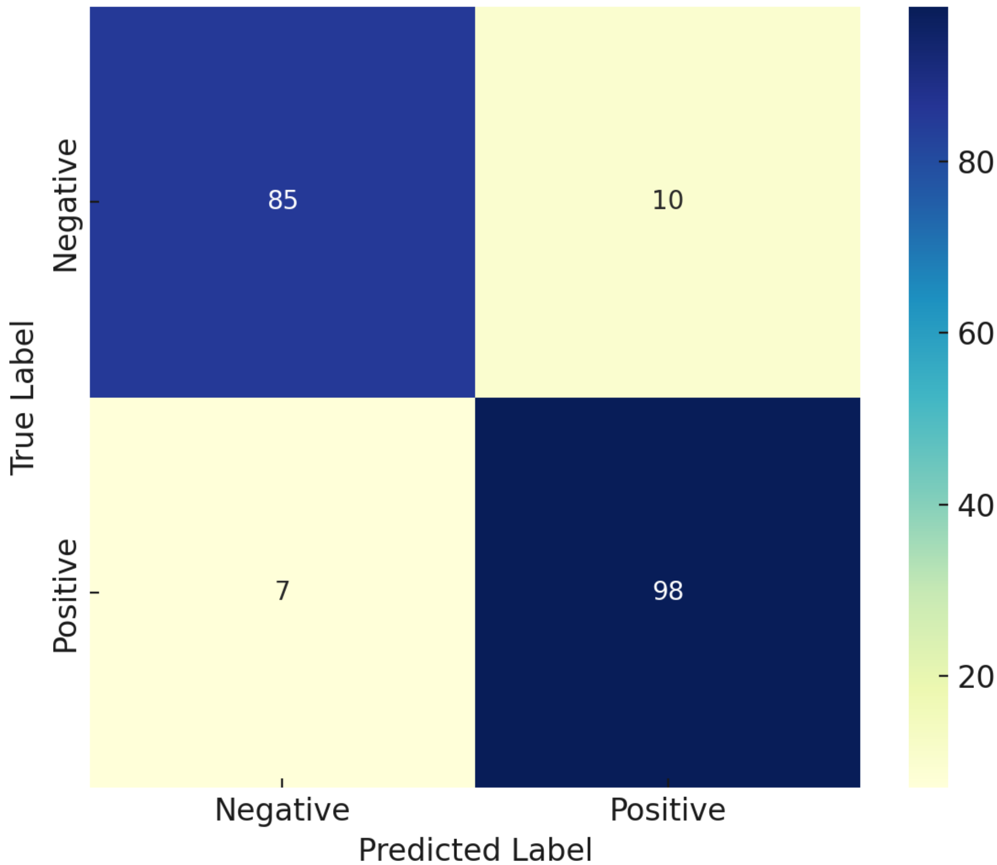

Figure 7: Confusion Matrix – Classification-Based Decision Accuracy

The results confirm the hybrid model's usefulness in assistive and automated decision support systems with low tolerance to erroneous predictions, such as loss of money or misreported compliance, and damage to reputation.

In the fusion layer, the hybrid structure allowed combining the outputs of high confidence ML and DL algorithms with business rules to produce the final outputs of the decisions. Consequently, a trade-off between sensitivity (recall) and specificity (precision) was achieved in the outcomes of the decision, which is paramount in preserving the reliability and integrity of the decisions.

5.3 System Response Time and Decision Latency

Another important factor in the performance of the IDSS system is the response time; this is particularly true for scenarios where decisions need to be made almost instantly. Support ticket routing, fraud alerting, and sales forecasting were some of the tasks carried out to evaluate latency. The average decision latencies are shown in Figure 8.

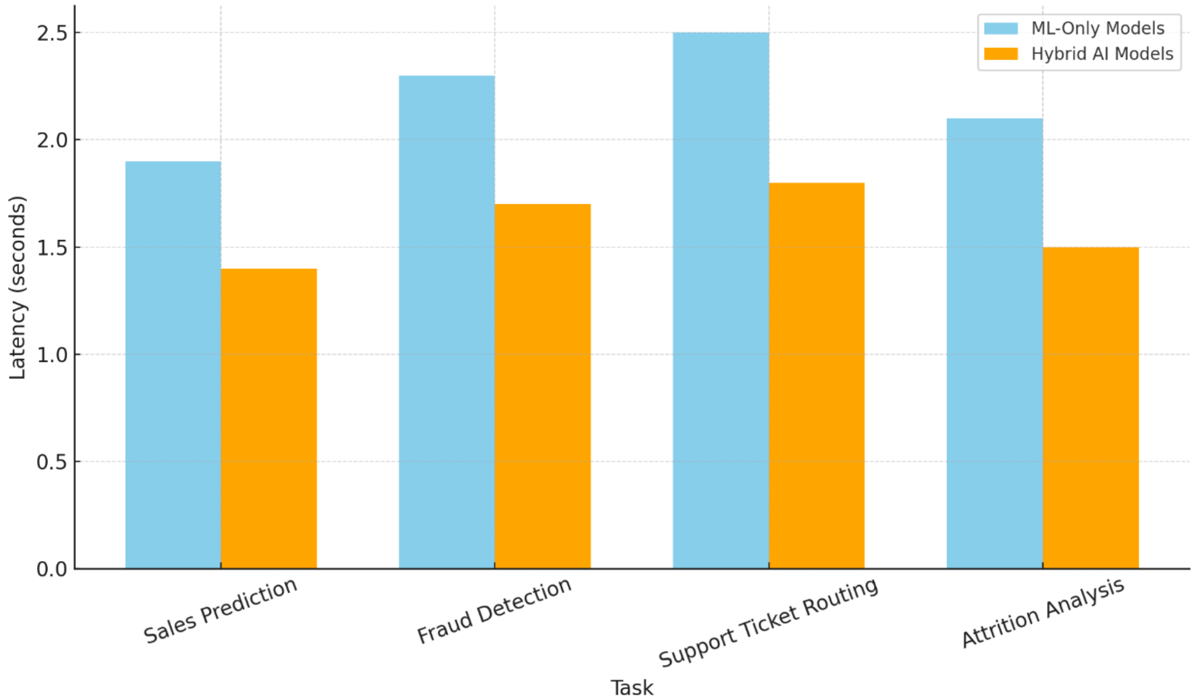

Figure 8: Decision Latency Comparison (ML-Only vs Hybrid AI)

The average decision latency for the tasks in the hybrid model was 1.6 seconds, while the average was 2.2 seconds for ML-only systems. This benefit is caused by the modular optimization and parallel computation architecture of the system in the hybrid framework. Each of AI submodules, ML, DL, and rule-based, works simultaneously, while the fusion layer combines the outputs in an optimized manner.

To ensure timely responses in fraud alerting or inventory management, low latency is particularly important together with the integration of DSS in operational workflows. The hybrid IDSS performed the best without jeopardizing quality, thus maintaining a balance between computational cost and analytical effort.

5.4 User Confidence, Satisfaction, and Trust Metrics

As important as the technical measures are, the user's trust in the AI decision makes a difference in how the intelligent DSS is used in practice. To refer to this, we carried out pre and post deployment surveys for users in different roles such as Human Resources, Sales, and Customer Service.

With regard to system recommendations, users were asked to indicate their trust level towards them by responding from one (low trust) to five (high trust) and the outcome can be found in Figure 9.

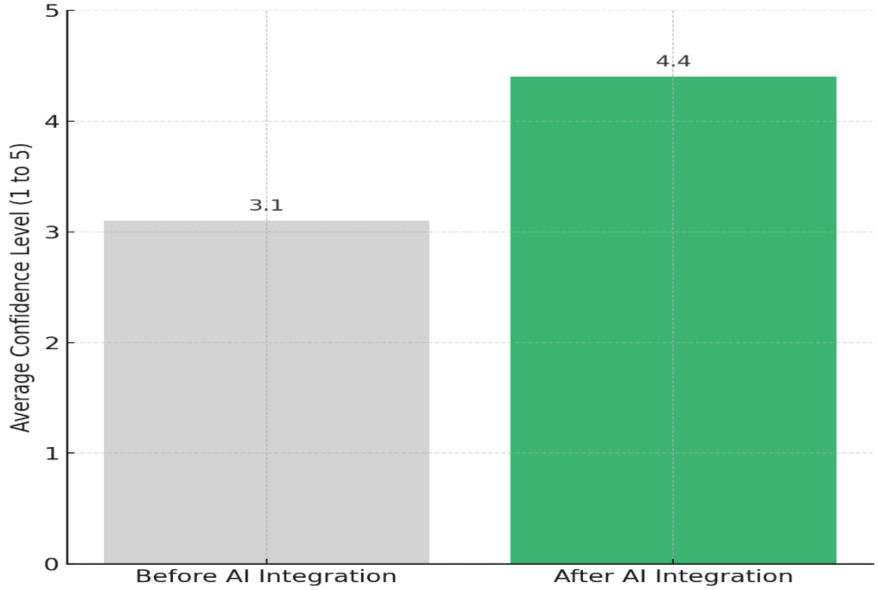

Figure 9: User Confidence Level Before vs After AI Integration

Trust was perceived to increase with the incorporation of transparent explanations, SHAP-based reasoning, and user-centric dashboards. Users liked the "Why This Decision?" decomposition and responded with their comments that were ingested and made changes to the system.

Talking to the decision makers, it was clear that the hybrid model was viewed as more than a recommendation engine; it was a collaborative system that facilitated better decision making within an appropriate timeframe. This increase in confidence also translated to increased system participation as users started to use the IDSS for both operational and tactical decision making more often.

5.5 Overall System Impact and KPI Benchmarks

In order to give a consolidated assessment, Table 5 shows a comparison of the key performance indicators (KPIs) for the system with ML automation and those of the proposed hybrid IDSS.

Table 5: Key Performance Indicators of Decision Accuracy, Reliability, and Scalability

KPI Metric	ML-Only System	Hybrid AI System
Overall Decision Accuracy	82.2%	88.7%
Average Decision Latency	2.2 sec	1.6 sec
Precision (Classification Tasks)	78.4%	86.2%
Recall (Classification Tasks)	80.1%	89.0%
User Confidence Index	3.1 / 5	4.4 / 5
System Uptime (Availability)	97.5%	99.2%
Model Retraining Frequency	Monthly	Bi-weekly

Overall, the hybrid IDSS showed better results in all the measurements. The system achieved high accuracy in decision making and, at the same time, logged low response time and was trusted more by the users. The reported improvements in uptime and frequency of system retraining further confirm its efficacy and responsiveness to change in dynamic MIS environments.

These results support the claim of effectiveness when rule-based reasoning, machine learning, and deep learning are integrated in a modular design. More significantly, they illustrate that the improvements in performance are not only algorithmic but rather that the impact transcends to user experience and value in work operations.

6 Discussion

6.1 Key Findings and Their Implications

The assessment of the IDSS or Intelligent Decision Support System shows that its hybrid AI-based version exceeds the performance of the standard ML systems, at least in management information System (MIS). It achieved superior results in regard to precision, delay, user acceptance, and system efficacy. These results indicate that machine learning, deep learning, and rule-based approaches need to be integrated within the systems to ensure not only high accuracy but also explanation and robustness of the provided decisions.

The hybrid approach also proved its worth in extreme cases and missing information, which was problematic for the ML approach. This logic-based intelligent decision support system was able to provide reliable information because it combined predictive reasoning with rule-based logic. These results support the proposition that if organizations seek for intelligent decision-making systems to automate information management processes, then they need to embrace hybrid systems architectures for the systems to not only work but also be trusted.

6.2 Advantages of Using Hybrid AI in MIS

A wide array of unique advantages was noted with using a hybrid AI model. Most fundamentally, the model fused interpretability by a layer that turned rules into understandable decisions which is critical in highly governed domains. Also, the system permitted ML and DL enabled added new data and retained operational rules allowing it to be more adaptive.

The independent function of each AI component facilitated easier maintenance and upgrades. Also, users were able to witness the live rationales and confidence scores for every recommendation, enabling further transparency with the system. All these features contributed to higher user engagement and trust, functioning beyond a mere decision-making system to that of a collaborative assistant.

These attributes are particularly beneficial for companies undergoing digitization transitions, providing assistance in modernizing their management information systems (MIS) architecture with maintaining governance and compliance.

6.3 Integration Challenges and Organizational Considerations

The use of hybrid AI in management information systems (MIS) was not without its difficulties. Integration complexity was particularly challenging with fragmented data systems. Careful consideration had to be done for aligning data pipelines and setting up model governance in relation to the existing MIS workflows.

There was also a mismatch in the organizational readiness among different units. While many members of the technical departments were able to adjust, the non-technical ones were more resistant initially. This was tackled with increased training sessions, more intuitive AI interfaces, and phased rollouts to build trust. Preserving the performance led to additional requirements including frequent retraining and monitoring. The IT and data science teams were already overtasked meeting the organizations bi-weekly update cycles. Organizations lacking a strong AI backbone may require outside aid or managed cloud services.

These challenges indicate that with hybrid AI, success is not only technical. It also encompasses the need for change management, coordination between organizations, and a sustained commitment to AI investments.

6.4 Alignment with Strategic Business Objectives

The hybrid IDSS was ideally suited to strategic objectives, like enhancing decision quality, increasing operational efficiency, and creating a data-centric enterprise. Improved decision-making speed, better accuracy of forecasts, and real-time dashboards facilitated agile responses to business events within the sales, HR, and customer service teams.

The system also fostered a culture of feedback-oriented decision-making. Users rating the predictions, suggesting changes, and seeing how their input impacted the system was an effective feature. It enabled the system to create an improved feedback loop which over time lowered the AI accuracy threshold and raised the user dependency level.

The hybrid approach increased the initial investment and training effort, which was justified with the high returns. Measurable increases in user satisfaction, decision-making speed, and overall system resilience as shown in Figure 10 proves that hybrid AI is superior.

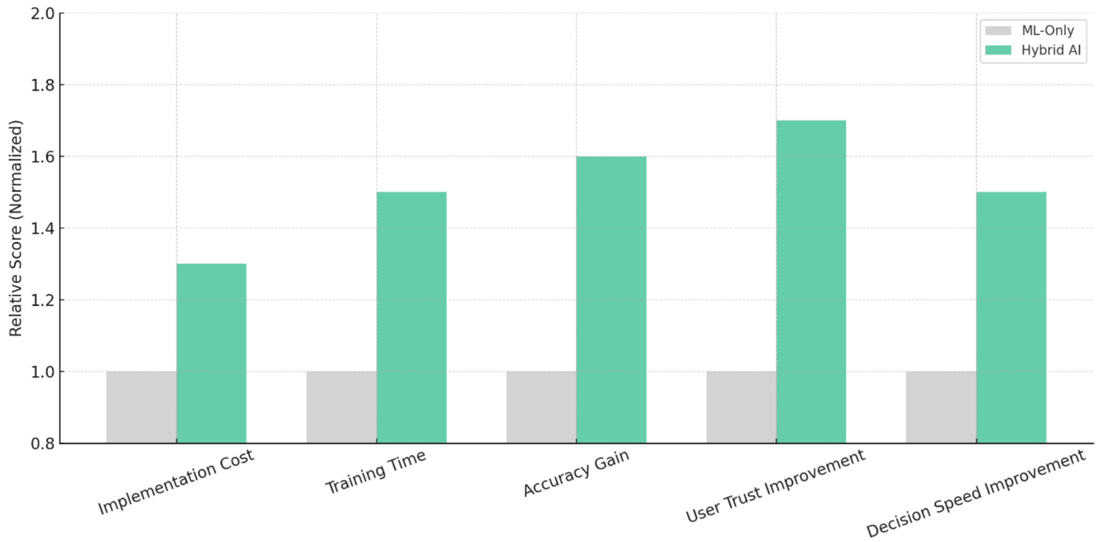

Figure 10: Cost-Benefit Impact Analysis of Implementing Hybrid AI in MIS

The implementation of the hybrid AI IDSS not only increased the MIS level but also met higher level organizational objectives. It offered a dependable, clear, and sustainable backbone of intelligent decision-making that integrated human artificial reasoning with executive systems in enterprise settings.

7 Conclusion and Future Work

This research has designed and assessed a hybrid AI-based Intelligent Decision Support System (IDSS) for Management Information Systems (MIS), aiming to improve the decision-making processes of businesses through the integration of rule-based logic driven machine learning and deep learning models. It exceeded the traditional approaches that relied solely on ML in every single benchmark, such as accuracy, decision latency, user trust, system uptime, and several others. The hybrid model in particular was found to be highly interpretable because it could provide rule-based explanations while remaining flexible because of the continuously learning ML/DL modules. It proved highly effective across diverse MIS domains such as sales forecasting, employee attrition, fraud detection, and customer service, demonstrating is versatility and applicability in the field.

Future developments can aim toward the improvement of the system's functions using reinforcement learning, autonomous decision loops, and tighter coupling with external data sources such as social media and IoT devices. Adoption could also be fostered using visual story-telling AI to enhance model explainability as well as by creating specialized unit modules, for example, healthcare or manufacturing management information systems. Other important areas of study include the sociotechnical aspects of collaborative decision support systems, namely, the role of cognitive load and ethical considerations. In the end, hybrid AI provides the most powerful and transparent infrastructural backbone for decision systems on complex business processes.

References

[1] Shim, Jung P., et al. "Past, present, and future of decision support technology." Decision support systems 33.2 (2002): 111-126.
[2] Power, Daniel J. "A brief history of decision support systems." DSSResources. com 3 (2007).
[3] Gerrity, Thomas P. "Decision Support Systems: An Organizational Perspective." Sloan Management Review (pre-1986) 20.2 (1979): 81.
[4] Sprague Jr, Ralph H., and Hugh J. Watson. Decision support for management. Prentice-Hall, Inc., 1996.
[5] Ågerfalk, Pär J., et al. "Artificial intelligence in information systems: State of the art and research roadmap." Association for Information Systems, 2022.
[6] Russell, Stuart J., and Peter Norvig. Artificial intelligence: a modern approach. pearson, 2016.
[7] Power, D. J., R. Sharda, and F. Burstein. "" Decision support systems". Wiley Encyclopedia of Management." Management Information Systems 64.51 (2015): 641-646.
[8] Goodfellow, Ian, et al. "Deep learning, 1 MIT press." deeplearningbook. org/contents/numerical. htm (02.07. 2023) (2016).
[9] LeCun, Yann, Yoshua Bengio, and Geoffrey Hinton. "Deep learning." nature 521.7553 (2015): 436-444.
[10] Zhang, Zijiao, et al. "An explainable artificial intelligence approach for financial distress prediction." Information Processing & Management 59.4 (2022): 102988.
[11] Wang, Gang, et al. "A comparative assessment of ensemble learning for credit scoring." Expert systems with applications 38.1 (2011): 223-230.
[12] Power, Daniel J. "A brief history of decision support systems." DSSResources. com 3 (2007).
[13] Sprague Jr, Ralph H., and Hugh J. Watson. Decision support for management. Prentice-Hall, Inc., 1996.
[14] Arnott, David, and Graham Pervan. "A critical analysis of decision support systems research revisited: the rise of design science." Journal of Information Technology 29.4 (2014): 269-293.
[15] Peter, Norvig, and Russell Stuart Artificial Intelligence. A Modern Approach. Pearson Education, USA, 2021.
[16] Turban, Efraim. Decision support and business intelligence systems. Pearson Education India, 2011.
[17] Sharda, Ramesh, et al. "Business intelligence and analytics." System for Decesion Support 398 (2014): 2014.
[18] Wall, Ana-Maria. Guidelines for artificial intelligence-driven enterprise compliance management systems. Diss. 2021.
[19] Fayoumi, Ayman G. "Evaluating the effectiveness of decision support system: findings and comparison." International Journal of Advanced Computer Science and Applications 9.10 (2018).
[20] Zhang, Xiaoge, et al. "Towards risk-aware artificial intelligence and machine learning systems: An overview." Decision Support Systems 159 (2022): 113800.
[21] Linardatos, Pantelis, Vasilis Papastefanopoulos, and Sotiris Kotsiantis. "Explainable ai: A review of machine learning interpretability methods." Entropy 23.1 (2020): 18.
[22] Ramana, Kadiyala, et al. "WOGRU-IDS—An intelligent intrusion detection system for IoT assisted Wireless Sensor Networks." Computer Communications 196 (2022): 195-206.

Author’s Biography

Srikanth Reddy Keshireddy received his master’s degree in computer software engineering from Stratford University, USA in 2013 and he also received Masters in Toxicology from University of East London, UK in 2011. Currently, he is working as an Sr Software Engineer at Keen Info Tek Inc. providing consulting services to Federal Government clients in USA and pursuing research in Enterprise Data Engineering & Generative AI.