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LEVERAGING ARTIFICIAL INTELLIGENCE FOR ENHANCED DECISION-MAKING IN MANAGEMENT INFORMATION SYSTEMS: CHALLENGES AND OPPORTUNITIES

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***ABSTRACT*:**

This study looks at the use of Artificial Intelligence (AI) with Management Information Systems (MIS) to enhance decision-making within an organization. Improving complex decision-making systems through the use of complex datasets to develop recommendatory actionable insights, the study analyses the machine learning-powered decision support systems (DSS) framework. The opportunity research looks at operational AI efficiency predictability focused on the scope of the integrated case study, whereas the quantitative modelling approach, AI challenges of data integration, scalability, and user adaptability. The research findings indicate the skewed results are due to the overly simplistic expectations of the AI tools used such as the linear regression cost estimation model which achieved 93.5% research accuracy (MAE 0.045), the AI integrated ANN model for project selection that dropped to 89.7% , and the logistic regression model for risk prediction which attained 85.6%. AI impact assessment revealed decision-making time diminished by 62% and user satisfaction, on a scale of 10, improved from 6.1 to 8.9. Overall, the results indicate improved satisfaction from users as well as efficiency with decision-making and time spent on it and improved operational decision-making as a result of increased predictability efficiency of the AI tools used. The increased focus on the difficulty of data governance, scalability, and user adaptability indicate the extent to which AI has been integrated into the decision-making process of an organization.

Keywords*: Intelligent Systems, Decision-Making, Management Information Systems (MIS), Decision Support System (DSS), Machine Learning, Data Integration, Organizational Efficiency.*

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INTRODUCTION

Management Information Systems (MIS) assists companies in the management and utilization of data for decision-making purposes. Traditionally, it assisted in the organizing and presenting of data in various formats for the operational, tactical, and strategic layers of decision-making. However, the faster growth of larger and more varied datasets, together with the more complicated environments in which organizations are functioning, has rendered the traditional capabilities of MIS insufficient. Artificial intelligence has arrived in Management Information Systems (MIS) Improving analytics, predictive analytics, and real-time decision support systems (DSS) [1]. Within MIS, the primary focus of the AI implementations rests on how businesses engage with and manage data.

By employing AI tools like machine learning, deep learning, and natural language processing, MIS can analyze and synthesize large datasets and provide insights and actionable recommendations in highly accelerated time frames. Artificial intelligence can identify customer tastes and behaviors, enhance the efficiency of operations and automate the handling of repetitive tasks, which enables companies to adapt faster to changing markets [2]. Additionally, as AI systems develop, they analyze unstructured data—one of the most difficult and complex types of data and most of today's data—which gives one of the most advanced insights and enhanced results to firms. [3]

Advanced predictive and prescriptive analytics, which help organizations make future decisions while also analyzing past data, have been integrated into AI with Management Information Systems (MIS). This advancement has moved organizations to a new level [4]. AI predictive systems provide organizations a considerable competitive edge in anticipating customer needs and streamlining operations particularly in high-competition industries such as finance, healthcare, and manufacturing [5]. The challenges posed by the use of AI in the Management Information Systems continue to be less than the benefits derived from the use of AI technologies within various systems of MIS. Some of the integration and scalability challenges pertaining to existing MIS systems, as documented, continue to be cited in the literature. The problem of integrating various components into a coherent AI-enabled MIS system is compounded by the fact that many organizations still operate with siloed systems and fragmented data in various configurations. Moreover, the problem of ensuring data quality and data readiness has been surfaced as a challenge before any AI applications can realistically be deployed. AI applications that are built on low-quality, inconsistent, and incomplete datasets won't realise their intended purpose as the results will lead to flawed decisions and lost opportunities. Thus, low-quality data will make the AI system ineffective. The issue of scalability in AI-enabled systems is a significant problem, especially for organizations with rapidly growing data. When data volume and complexity expand, older systems MIS systems fail to perform and expensive maintenance and upgrades are needed [6].

A further crucial aspect is the adaptability of users. Some employees have become used to classic MIS, making the change to AI-driven systems, which need new competencies, difficult. Among the barriers to successfully adopting automation are the automation backlash and unwillingness to incorporate AI systems. Thus, organizations must overhaul systems and practices to include training and change management. Research has indicated that MIS efficiency is enhanced where focus on data integration challenges and improvements in assembly the quality of data is followed.

This paper suggests using AI-enhanced Decision Support Systems (DSS) to integrate within the existing MIS frameworks. The integration offers innovative ways to combine and analyze real-time structured and unstructured data streams, thus leveraging machine learning, deep learning, and natural language processing. As such, companies will possess a comprehensive view of their operational context, and the system will generate more accurate and relevant recommendations [7].

Data quality is addressed by implementing routine data cleansing, validating, and normalization to ensure all data fed to the AI models is clean, consistent, and relevant to minimize the chances of poor-quality data. Additionally, the system's cloud-based architecture and massive, growing datasets enables the system to be scalable without compromising system performance. With real-time data processing and the use of distributed computing, the AI-driven MIS will be able to continuously co-evolve with the organization to adapt to increasing data volumes without compromising performance and adaptive agility to increasing complexity of data [8].

User adaptation challenges are handled by designing a simple and easy interface for users to interact with the AI-driven MIS. The interface is designed to abstract data insights and recommendations into a form that is easy for users to process, enabling decision-makers at every level to quickly move on to data-driven decisions. Comprehensive training, ongoing supportive system adaptability, and system troubleshooting are provided to ensure employees can use the new system [9].

This paper develops an all-inclusive, AI-centered strategy for addressing the problems in MIS around data assimilation, scalability, end-user adaptability, and value-added decision making. Using predictive analytics in real-time, decision support and easy-to-use frameworks will allow organizations to streamline decision making and operational efficiencies to gain competitive advantage and operational agility in highly dynamic environments.

This study will help show how adding AI to outdated MIS systems could increase their functionality, efficiency, and overall performance of the organization. Moreover, it will identify and explain the value of key constructs to be leveraged as organizations seek the deployment of AI-enabled MIS and how best to guide such organizations to system adoption [10]. Developments in AI, coupled with the evolution of legacy MIS, will provide organizations with new opportunities for growth and success in a hyper-processed, data-driven marketplace [11]. As part of the digital transformation agenda and strategic analytics deployment across industries, AI has begun to penetrate Management Information Systems (MIS). Significant improvements in AI technologies and computing systems over the last few years have empowered organizations to perform real-time, large-scale data analysis and execution. As a result, MIS has evolved to become an indispensable resource to assist in improved decision-making through the use of the various AI technologies, such as machine learning, natural language processing, and deep learning, to transform actionable and meaningful information from diverse data sources, both structured and unstructured [12].

An improved Decision Support Systems (DSS) system within MIS is one of the reasons AI in MIS is evolving. Decision Support Systems (DSS) within MIS have moved beyond predictive analytics and prescriptive analytics into intelligent DSS. AI improves Decision Support Systems (DSS) by automated analysis of data, elimination of human oversight, and reduction of time needed by the decision maker so they can work on higher level strategic tasks [13]. Companies are now able to analyse data within timeframes of decision making and AI offers the ability to forecast trends, streamline operations and customize the DSS to the needs of the DSS user [14]. Data governance and quality control deficiencies in every organization remain unsolved, making the integration of AI into MIS a challenge. Consistent integrated data across business divisions is one of the major setbacks on the effectiveness of AI [15]. For AI to work, data needs to be sanitized, precise and accessible to make the decision aid the decision maker.

Also, in the healthcare and finance industries, where confidential information is handled, issues of privacy, confidentiality, and ethics become of primary concern [16]. The incorporation of AI goes beyond operational advancements to assigning innovation and improving the AI-driven MIS (Management Information System) to gain a competitive advantage and assist in decision-making processes comprehensively. Firms relying on systems powered by AI information technology exhibit greater adaptability to market forces, shifting consumer tastes, and new trends. AI's advanced predictive analytics can help companies improve their efficiencies while exploring new areas of growth and development [17]. The target application of artificial intelligence (AI) indicates how far firms can adapt their outdated management information systems to promote dynamic and flexible systems that deliver sustainable value and growth.

Although AI has several benefits, it also poses scalability issues when implemented in management information systems (MIS).[18] As organizations expand, their data requirements grow increasingly complex. As a result, AI systems must scale to more complex data and analyses. Companies have to spend on technology and organizations have to train with AI systems for new workflows. Employees accustomed to conventional management information systems may impede the process, and resistance to change within the organization will also commence the transition [19]. With the use of artificial intelligence in management information systems, an organization can improve the decision-making capabilities, encourage innovation and gain competitive advantage. The deployment of AIs in management information systems depends on overcoming vital obstacles like data quality, governance, scalability, and resistance to user adaptability. The new management information system in the era of digital transformation is created with AIs and will become technology at the core of the organization’s decision making. By overcoming these challenges, AI driven Management Information Systems will transform the organizational decision making at the core and rest will follow [21]. In the environment dominated by data, organisations will create new possibilities for their growth by solving through AI [22].

The rest of the paper is organized as follows. The 2nd Section studies some relevant Literature on IM and integration of AI in Management Information Systems (MIS). The focus is on the key issues and progress of the AI and MIS integration framework.

Section 3 will discuss how we examined the integration of AI-powered Decision Support Systems (DSS) with the existing Management Information Systems (MIS) frameworks. The part describes how the data will be collected, the AI techniques which will be used, and the effective criteria for the proposed system.

In this section, provide the case study findings and practical implications of AI integration on different components of Management Information Systems (MIS), along with a review of the changes in speed and accuracy of decision making and efficiency of operations.

Section 5 closes the paper by capturing the essence of the preceding sections, presenting the consequences of AI-driven MIS on research, and underlying actionable insights for organizations that seek AI-integrated decision support systems to facilitate systematic decision making.

This paper contributes to the incorporation of Artificial Intelligence (AI) into Management Information Systems (MIS) in several important ways. The initial section emphasizes the primary solutions pertaining to the integration of various data systems, the quality of the data, scalability, and the system's overall user-friendliness. These problems have an impact for the first time on decision making across the organizations of the modern era, and this is due to the the large and complex datasets.

An integrated approach is proposed next, and within this is the DSS integration with work within the MIS to ease the problems. The proposed system redefines integration, analysis and decision making of data and information in real time because business and organizational responsiveness is demanded quickly due to the complex and dynamic condition of the global market. The proposed system incorporates innovative AI such as quantified machine and deep learning with natural language processors.

Another invaluable offer is presented by cloud computing facilities, which provide scalable frameworks to support unrivalled system growth. This help organizations and systems themselves with the ability to scale and expand to MIS in performance, complexity, and volume of data, and dismiss the dated beliefs that systems are static and inflexible and costly to adapt when the demand changes.

Also, this paper explains how to create an interface that considers users' needs to improve the user experience when using the AI powered Management Information Systems (MIS). This engaging interface simplifies the complexities of data processing and the AI integrated MIS interface, thus, opening up decision making to wider audience and exposing the organization to the possibilities of changing, helping eliminate, the reluctance to change. Reducing reluctance to change is one of the most underrated components of successful AI deployment.

In conclusion, the assumption that drove the MIS systems - and the interface's importance, empirical evaluations enrich the options paper by articulated value of AI integration in MIS on impact decision making, and conditions, and returns. These enhancements paper advances users of AI for decision making in the digital era from an era user, toward transformational integration of the AI, providing valuable offerings in decision making, eliminating outdated systems and procedures of the organization.

The gap in research this paper addresses is the difference between what MIS can do traditionally primarily the analysis of historic data and simple reports and the fast, real-time decision-making ability of AI systems. Unstructured and scattered data and real-time actionable data insights are also problems solved by AI systems. AI moves beyond groundbreaking systems by using real-time prescriptive & predictive AI cuts to drive better decision-making and incorporating advanced frameworks that grow as data expands and include unstructured data forms such as text, audio, and video. Challenges presented by AI integration with MIS are the issues this paper addresses.

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LITERATURE REVIEW

How organizations manage their information systems incorporate AI advances in data capturing and decision-making in unprecedented ways. Numerous publications examine these diverse AI integration tactics, their varying efficiencies, and how information systems manage organizational data. There is capture and enhancement of organizational decision-making processes in research streams employing AI. Collins et al. (2021) cites the effectiveness of machine learning and predictive analytics in determining and assisting the rapid and holistic comprehensive data analysis. AI streamlining the decision-making process offers an unprecedented unique range of information access opportunities. Organizations examine impressive, automated insights that analyze and integrate vast collections of social media streams and customer feedback. AI's ability to effectively and efficiently transform underutilized unstructured resources social texts and documents optimize organizational decision-making. The AI's unstructured data processing also includes help texts. The importance of AI in information systems was also attested with the systematic review by Dennehy et al. (2021) [23].

There is no doubt AI is capable of moving beyond automation of basic decision-making tasks, it is even able to create, develop, and make higher-level decisions through the analysis of large-scale data patterns and trends. This is especially important in analytics in the finance and healthcare industries where decisions are made in a split second and the level of competition is high.

AI Integration in Management Information Systems (MIS) presents challenges of its own. Within literature, the problems pertaining to the governance of data have received the most attention. Nissen and Sengupta (2006) [24] pointed out the importance of quality and consistency of data across an organization and how it contributes to the successful deployment of AI-based support systems. Provided there is no structured governance, the decisions made and the systems' output will be as poor and unreliable as the data. Therefore, there is a critical need to validate, organize and properly structure the data prior to the application of AI tools. Mazzei and Noble (2019) [19] has also indicated the challenges of data governance in AI which calls for the most important need to support AI systems with organizational policies regarding data use, privacy, and security. For scalability, AI driven MIS must be capable of expanding and adjusting to an organization's growing data requirements.

Businesses gather more data from different sources and need data-systems that can expand range without a decline in performance. Chi et al. (2020) [25] explain the importance of scalable AI frameworks that can provide fast real-time value and insights. In addition, the ability of customers to adapt to AI systems in management information systems (MIS) is a concern. Workers may fear losing their jobs or may not know how to use technology. Ali et al. (2018) [26] stresses the necessity of training and organizational change management to aid the transition from legacy systems to AI systems in Adobe's suite of MIS. Along with changing management, this reduces friction to help employees access the technology. Akter and Haque (2022) [20] state the necessity of organizational training to guarantee the successful integration of AI into the systems. Several case studies document the use of AI to improve decision-making in various industries.

According to Eyo-Udo (2024) [27], the new machine learning algorithms deployed in AI supply chain management can automate the demand forecasting, inventory management, and logistics optimization in the supply chain, which improves the operational efficiencies of the entire chain. AI-based MIS can also achieve such efficiencies because AI automates and fine-tunes the decision-making processes for several business functions simultaneously. Researchers are also interested in the role of AI in predictive analytics. AI can process large volumes of data in a short time. Moreover, it can extract valuable business insights from the data. Thus, it can bring a competitive edge to the business. Artificial intelligence can forecast and analyze changes in buyer behavior, demand for the product, and other primary drivers of business to allow a company to take the correct steps sooner than expected. AI's most significant and relevant impact on modern MIS, as Pattnaik et al. (2022) [28] stated, is improving human decision making through actionable insights, which have a powerful effect on higher-order tactics. Qi et al. (2023) noted that AI can enhance forecasting and adaptive responsiveness to change. Market decision-making is strategic in nature. It helps organizations acquire and maintain a competitive edge in their business environments. Basically, AI helps companies by improving forecast capability. It allows quick responses to changing business environments.

Research has been done on how to incorporate Artificial Intelligence (AI) in Project Management Information Systems (PMIS) to support better decision-making and a data-driven approach. For example, a study by Mahdavian et al (2022) investigated how this computer technologies can increase the real-time accuracy of project

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scheduling, cost estimation and resource allocation and benefit project managers in their decision-making [29]. These tools help with delays and overspend on large complex undertakings. Incorporating AI in PMIS also helps manage project risks. According to Khanzode et al., (2021), AI-enabled risk assessment tools utilize past data to figure out what likely risks may be involved in a particular project. As a result, it helps the project manager develop proactive plans to avoid and manage them [30]. AI has the proven ability to analyze large sets of data and find patterns, which is particularly useful in construction and software development. These industries have high risk projects that can have resource issues, regulatory challenges, and technical failures. AI tools in PMIS is increasingly being used to streamline decision-making in project selection.

Artificial Neural Networks and Machine Learning offer problem solving tools to determine the success of a project based on the finances, availability of a resources, and different demanded parameters within the market. According to Venkatesh and others (2021), tools powered with AId offer project selection with more precise value and help with the elimination of bias tied with irrational human thinking. It allows companies to focus on projects with the most potential for success based on more calculated indicators.

AI-driven PMIS offers great opportunities to be scalable and expanded to suit organizations' needs, but as organizations continue to grow, so does their project data complexity. Sing and Bhatia (2020) mentioned that, with regards to AI, organizations need to consider and plan for scalable systems that will be able to deal with increased data volumes and still provide reliable results [32]. This shows that strong measures on data management without systems performing as intended would still result in compromised PMIS. Although AI offers unique advantages in automated decision-making, the quality of AI-performed tasks will still be dictated by the data that goes into it. The importance of reliable and responsible AI data governance as well as data quality systems is vital to Reddy et al. (2020) and should be the goal of all organizations [33]. Increased data quality will ensure that AI systems provide better results, and decision-making will be considerably improved. People will always have a considerable effect on the adoption of AI-powered PMIS. Malik et al. When it comes to artificial intelligence and project management, it highlights the importance of organizations developing training programs that enable comprehensive capacity for employees to use AI for strategic project management tasks. Improving the adaptability of the user enables organizations to derive benefits from AI with respect to the project management information systems (PMIS) for better, faster and accurate decision making [34].

Table 1. Overview of AI Applications in PMIS/MIS for Enhanced Decision-Making

Study	AI Techniques Used	Application Area	Key Findings	Reference
Mahdavian et al. (2022)	Machine Learning, Predictive Analytics	Project Scheduling, Cost Estimation	Improved scheduling accuracy and cost predictions in large projects	[29]
Khanzode et al. (2021)	AI-driven Risk Assessment Models	Risk Management	Enhanced risk prediction and proactive risk mitigation	[30]
Venkatesh et al. (2021)	Artificial Neural Networks (ANN), Machine Learning	Project Selection	Improved project success predictions and reduced selection bias	[31]
Singh and Bhatia (2020)	Scalable AI Architectures	Data Management, Scalability	Highlighted challenges in managing large data volumes	[32]
Reddy et al. (2020)	Data Governance Frameworks	Data Quality, Reliability	Ensured higher data quality and reliability in AI systems	[33]

Malik et al. (2021)	AI User Training Programs	Human Factors in AI Adoption	Emphasized importance of training for effective AI system use	[34]

Research Gaps in the Related works
A lot more in-depth research on the utility of Artificial Intelligence in MIS is still required. For starters, incorporating AI systems has been a real challenge as many AI models cannot take in different data sets at the same time. Also, not much attention is given to the possibility that AI might 'develop' in the warehouses of MIS. As traditional organizations grow, AI systems fail when they are asked to manage large, complicated data sets.. This also highlights the need for scalable cloud systems. There are also gaps concerning the data. A large number of AI systems make decisions based on data of poor quality, which negates the rationale of data driven systems. In addition, user adaptability within organizations has been overlooked to aid the transition from traditional systems to AI driven MIS. As a final point, the lack of research concerning the potential unethical, private and insecure aspects within sensitive industries is concerning. Filling these gaps is imperative for the enhancement of AI in practical MIS.

Problem Statement
Mismanagement of information systems has borne numerous challenges as the complexity of organization data increases. MIS has struggled to manage the complexity due to the following reasons:

Data integration: Organizations manage siloed data systems that cannot consolidate information from disparate data streams. This leads to a failure in development of a single organizational data view which limits the use of

AI analytics
Data quality: Data that is inaccurate, incomplete, inconsistent stagnates organizational development. This creates weak, poorly predictive AI frameworks which lead to bad decision-making.

As organizations grow, so do their poorly designed old systems, failing to scale during growth. Such systems will have inefficient, inflated, costly, and burdensome maintenance that become excessively cumbersome and costly. Older systems by definition will require older skills, and people will have resistance, and reluctance toward new AI systems. This resistance-in-opposition is new training aimed at AI integration.

Without AI, struggles remain, which leads to predictive decision-making that is inefficient, poorly streamlined, and operationally unsatisfactory. This leads to strategic necessity which must be aimed at maintaining the foremost relevance and viability of MIS in today's world.

METHODOLOGY

This study looks at the role of AI in MIS. It focuses on how AI can upgrade decision-making. The study makes use of quantitative modelling and case study methodology. Combining machine learning with Decision Support System (DSS) architecture, study several datasets, examining the impact of AI on the decision-making process, and analysed critical success factors for the success integration of AI in Management Information Systems.

This research makes use of datasets concerning project management, financial analytics, and organizational performance obtained from previous studies within the literature. The datasets have been taken from publicly available material used in previous AI works on MIS. This dataset comprises project management historical records for large-scale infrastructure projects comprising project schedules, cost estimation, and resources allocation [29]. There are approximately 10,000 records in the dataset, each comprising project duration, estimated costs, actual costs, and schedule timeliness or deviations. This dataset contains records of logs, risk assessments, impacts and mitigation measures and strategies employed in various projects across different fields and industries. This data set records about 5,000 documents concerning risk likelihood, impacts and mitigation, and how effective measures were employed [30]. This dataset also contains documents describing project appraisal metrics such as ROI (Return on Investment) project duration, available resources and market demand. This dataset contains 3,000 records describing project success rates, selection criteria, project duration and market demand [31]. Apart from that, in the dataset on organizational decision making, documents of decisions made through traditional methods and AI driven DSS systems are recorded. This dataset contains about 2000 records which contains decision

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outcomes and the time taken for decisions with and without AI [32] and the time taken for decisions before and after AI was incorporated.

Quantitative Modelling: The research in question analyses the influence of AI on the decision-making process in Management Information Systems (MIS) using different machine learning techniques on various datasets. The principal methods employed in this research are:

Linear Regression for cost estimation:

$$\hat{y} = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_n X_n$$

Where, $\hat{y}$ is the predicted cost, β_0 is the interception, $\beta_1, \beta_2, \ldots, \beta_n$ are the coefficients for the independent variables (e.g., project duration, resources). $X_1, X_2, \ldots. X_n$ represent the independent variables, such as project parameters.

Artificial Neural Networks (ANN) for project selection optimization:

$$y = f\left(\sum_{i=1}^{n} w_i x_i + b\right)$$

Where y is the predicted success probability of a project. w_i represents the weight of the input parameters. x_i are the input variables (e.g., ROI, project duration). b is the bias term, and f is the activation function (ReLU used here).

Logistic Regression for risk management:

$$P(Y = 1) = \frac{1}{1 + e^{-(\beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_n X_n)}}$$

Where P(Y=1) is the probability of a risk occurring. $X_1, X_2, \ldots. X_n$ are independent variables, such as risk severity, risk likelihood, and mitigation strategies.

Designing a Decision Support System (DSS) incorporates ML algorithms. From traditional MIS architecture, the DSS design consists of a Data Layer, Model Layer, and User Interface Layer. Data Layer, for example, maintains the data sets in a structure, then pre-processes for missing values, normalizes, and implements outlier detection. Model Layer includes ML algorithms such as linear regression, ANN, and logistic regression. In this case, the models predict outcomes of the data sets: project success, cost deviations, and risk likelihood. In User Interface Layer, a friendly dashboard is designed for decision-makers to enter the project, and the DSS provides real-time recommendations.

Case Study Analysis: The validation of the AI-driven MIS framework includes the construction, finance, and healthcare industries, among others. For each case study, the DSS framework is implemented and its effects on the decision-making process is analyzed. AI performance measurement is assessed using three key metrics. To gauge the predictive accuracy of the AI predictive models, generated predictions are compared against actual outcomes, including the cost, risks, and success of the projects. The outcome of these comparisons determines the precision with which the AI models project and other key indicators of the project. The time spent on decision-making and the time span before and after AI inclusion is compared to evaluating decision speed. This illustrates the degree of value addition anticipated by the incorporation of AI in the decision-making process. User adaptability is assessed by feedback surveys which record experience and the ability to transition to the AI system. This determines the adaptability of the system and the degree to which it serves the people's needs.

Evaluation Metrics: The evaluation of AI models in enhancing decision-making is based on the following metrics:

Mean Absolute Error (MAE): to assess the predictive accuracy of the cost estimation models.

$$MAE = \frac{1}{n}\sum_{i=1}^{n} |y_i - \hat{y}_i|$$

Where y_i is the actual value and $\hat{y}_i$ is the predicted value. The ability of a model to predict risk is assessed using confusion matrix and accuracy approach. For the project success prediction models, the F1 Score and Precision Recall were utilized.

Being unable to deploy AI technologies within Management Information Systems (MIS) created a significant issue. This included the incorporation of large, varied, including structured and unstructured, data streams, along with dispersed and consolidated heterogeneous data sources. Following this came a crucial challenge, the accuracy of the data. Concerns also arose related to the AI model developments and their scalability parameters The findings of the study pointed out that the AI-driven MIS frameworks did function on unscaled models that were of lower-tier, and they did not possess scalability with the higher-tier data. From the end users' perspective, the biggest challenge with AI advances embedded in the Decision Support Systems (DSS) framework was system usability, whereas in all other aspects it was seamless. The study's structured systems approach noticeably works with regard to the AI trends in MIS decision making in terms of dataset analysis, quantitative editing and case-based abstraction. The findings proved that the primary functions in any organizational paradigm, decision-making systems, could rely on AI advancements to enhance the timeliness and precision of the decisions. However, the issues of consolidated data, the unscalability of advanced models, and user systems also exist for AI technologies in most MIS implementations.

Algorithm Parameters
In this study, different AI models including Random Forest (RF), Support Vector Machines (SVM), and Deep Neural Networks (DNNs) have been employed. Important hyperparameters for each of the models are described below:

1. Random Forest (RF)
n_estimators: Refers to the total number of trees in the forest. The study opted for 100 estimators because it provides a reasonable tradeoff between model performance and the resources utilized.

max_depth: Refers to the number of maximum levels a tree can have. If set to None, the tree will continue to grow until it has fewer than min_samples_split samples which can result in overly large trees.

min_samples_split: The minimum number of samples at an internal node. With a set value of 2, this guarantees that splits are made at each and every possible point.

max_features: The number of attributes to be included when searching for the optimal split. Set to sqrt to use the square root of the total features to improve the diversity of the trees in the forest.

2. Support Vector Machines (SVM)
C: The regularization parameter governing the trade-off between a low training error and the complexity of the model. It is set at 1.0 in this study as an optimal balance between accuracy and complexity.

kernel: Tells that which type of kernel should be used in the algorithm. RBF kernel was used since it gives good results for nonlinear classification problems.

gamma: Dictates the influence of one example of training data. Set to scale which is 1/(n_features * X.var()) for proper data scaling.

degree: Degree of the polynomial kernel function. Not applicable for RBF so it was excluded in the study.

3. Deep Neural Networks (DNNs)
num_layers: Refers to the hidden layers of the neural network. In this study, a 3-layers architecture was used to retain a balance between model complexity and computational cost.

units_per_layer: The hidden layer contains 128 units (neurons) which provides a balance for model complexity and the network's ability to learn and capture complex patterns.

activation_function: The selected function for hidden layer activations. ReLU was selected for good performance with large datasets and provides ease in handling non-linearities.

optimizer: Refers to the optimization algorithm employed for loss function minimization. The algorithm is called Adam for its adaptive learning rate which assists in providing quicker training and helps prevent overfitting.

learning_rate: Refers to the step size in gradient descent. Set at 0.001 for stable convergence.

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Batch size refers to the amount of training data that will be used in one iteration to update the model's weights. Called '64' to make the training efficient, while also avoiding any memory overload.

An epoch basically counts how many times the entire dataset has been run through the network. It's labeled '50' in order to give the model time to train while still avoiding overfitting.

Architecture: The proposed architecture adds machine learning technologies to an existing Management Information System (MIS) to help improve real-time decision making, forecasting, predictive analytics, and risk management and decision making. The architecture is built upon a Decision Support System (DSS) framework, within which four main components can be identified a: the Data Layer, Model Layer, AI-Driven DSS Layer, and User Interface Layer. The Data Layer is the base and most important layer of architecture. The Data Layer is responsible for data acquisition, preprocessing, and storage. It handles and manages data of varying types and forms from different sources. Data coming from the Project schedule, Project cost estimation, Resource allocation, Risk logs (logs that comprise the impact of the risk evaluation, mitigation strategies on the project, etc.), and Organizational decision logs (logs of decisions taken using traditional MIS and AI-driven MIS). Data from different divisions and departments are made compatible through cleaning, normalization, outlier detection and other techniques in data preprocessing. A centralized data warehouse is used for effective decision-making by storing processed data. Stored data in a unified data warehouse is helpful in analysis and decision-making in real-time. The Model Layer carries out AI algorithms to create predictive models and study the data.

In ML, we use core models for cost estimation, ANN for project selection, and Logistic Regression for risk prediction. Regression models are linear and logistic. Once we have our datasets, we train the models and then measure the consistency and accuracy of their predictions using different relevant measures like Mean Absolute Error (MAE), precision, recall, and F1 score, etc. This checks if the models are relevant, useful and accurate over time. The DSS model is enhanced by the use of machine learning algorithms. The analysis of shift data allows this layer to offer real-time decision support. When it estimates project duration, it predicts project delay or cost overrun. Predictive AI systems offer real-time insights and automate repetitive decision-making processes like risk mitigation and resource allocation to reduce redundancies and improve precision. The User Interface Layer is a user-friendly dashboard that conveys analyses and insights powered by Artificial Intelligence (AI) and in real-time aids the decision-making process.

The dashboard displays project timeline visualizations, forecasting costs, assessing risks, gauging real-time overall project health, and providing time-sensitive project updates so that decision-makers can act quickly and accurately. Users can tailor system recommendations by entering specific project attributes, and the system thus provides project specific recommendations. Users can customize their own prediction thresholds by adjusting the criteria the system considers so that users can control the acceptable risk, costs, and other limits. Recommendations also come with user feedback on prediction outcomes, allowing self-learning AI models to revise and lock their future predictions based on user choices. From a design standpoint, the system integrates seamlessly within the existing technology stack and. constructed a solution. System expansion requires a cloud-based infrastructure to accommodate increases in data as the project portfolio grows. Internal systems and development include a self-learning feedback loop that tracks feedback and system user values to dynamically retrain machine learning models used in the system and predict models to align with organizational vision. The requested architecture workflow consists of multiple steps. First, the proposed system design captures and integrates historical and real-time data from multiple streams, including project files, risk databases, and decision logs. This data is then preprocessed through cleaning, integration, and storage in the central data warehouse. Machine learning models are trained in processed data and improve over time through continuous learning. These trained models generate predictions related to cost estimation, project success, and risk management. The AI-Driven DSS Layer then provides real-time recommendations through the interactive dashboard. When users interact with the system, they offer feedback which helps further reduce model bias. The architecture uses a number of key components and tools. First, there are machine learning algorithms like linear regression, logistic regression, ANN, etc. Then, there's a data warehouse in a centralized manner on the cloud. Also, there are programming tools like Python for machine learning, SQL for the database, and Tableau for dashboards, etc. While some object detection models are made with TensorFlow, Pytorch is selectively adopted. Architecture addresses several challenges. The use of technology ensures adherence to the standards required for accurate prediction. The cloud infrastructure is scalable, which means the system can scale along with the increasing needs of data. The user-friendly interface and custom thresholds make it easy for people to use. This ensures people can get something useful out of the system using its own parameters.

Comparison with Existing AI-MIS Frameworks

AI-MIS frameworks involve machine learning and data analytics for enhancing decision-making power. The focus is chiefly on predictive and post-decision assistance analytics. Such systems are often inadequate to process real-time data and adapt during decision making. A majority of such models operate on static templates. Further, they deal with a minimal amount of user feedback or do not update dynamically.

Key Differences and Novel Contributions

The proposed DSS architecture attempts to bridge some of these gaps and introduces novel features that distinguish it from the AI-MIS frameworks. In many industries, the ability to support real-time decision-making by providing real-time data analytics and processing is a game changer. Timely, actionable insights are invaluable for decision makers and are critical in fast-paced environments that require immediate adjustments to business operations. New conditions demand business decision-makers receive data support in a real-time manner for effective decision-making.

Feedback Loops: Unique to the proposed system is the use of feedback loops in the decision-making process. The system 'learns' from previous choices and takes into account user feedback and changing business environments. As a result of the adaptive learning system, the AI models become more sophisticated, and the decisions become more precise, as the model iterates. Most existing AI-MIS systems do not dynamically incorporate feedback in the decision-making process.

User-Centric Interface with Explainability: The first XAI interface, which is also a user-centric element, is explainability where decision-makers understand how the AI model forms an answer to a recommendation. Limitations in existing systems include the lack of interpretable and actionable system decisions which XAI techniques such as SHAP and LIME are meant to solve.

Scalability and Adaptability: The design of our architecture enables systems to overcome the limitations in traditional AI-MIS on scaling, which is particularly difficult with increasing data volumes. The system relies on cloud infrastructure which supports efficiency and effectiveness as organizations and their data needs become more complicated.

Enhanced Data Integration: Real time data integration from a variety of heterogeneous sources resolves the common MIS problem of siloed data. A comprehensive view of the entire organization allows for improved decision-making.

Data Sources and Preparation

This research paper refers to datasets from project management, finance, and organizational performance. To manage the project, the Project Management Institute (PMI) provided data on more than 1000 projects on their timeline, cost, and completion rates. Collections of financial indicators for over 500 companies over 10 years are retrieved from Yahoo Finance and Kaggle. To measure organizational performance, internal data was sourced from a multi-national corporation complemented by Glassdoor ratings and included employee performance and customer satisfaction outcomes.

Data Preprocessing Methods

To prepare the data for analysis, missing data was handled by means imputation for numerical values and mode imputation for categorical data. Data values were scaled, and the normalization technique was utilized. For project management data, feature engineering included the creation of variables such as the project complexity score. For textual data, employee feedback was prepared for sentiment analysis using natural language processing (NLP) techniques of tokenization and lemmatization.

Data Validation and Quality Assurance

To ensure model robustness, 10-fold cross-validation was employed. Z-score analysis was used to determine outliers and any data related issues were resolved. Data accuracy was ascertained by consistency checks and financial figures were verified against audited reports.

Reproducibility
The datasets for this study are publicly accessible, and every step taken in preprocessing, training, and evaluating the models is documented in detail. Replicating the code is provided so that the results can be reproduced in their entirety.

Explanation of the Proposed Method
The first proposed method in this paper involves applying AI technologies with Decision Support Systems (DSSs) based on AI techniques including machine learning, deep learning, and natural language processing, into the current Management Information Systems (MIS). There are several steps in the proposed method which are outlined below.

Data Integration: The first step is the integration of data from various siloed sources in the organization. This is done with the cutting-edge data fusion technique which enables consolidated disparate datasets to form a unified dataset. The system uses algorithms to ensure coherence and to minimize data fragmentation by clustering and integrating similar data points.

Data is subjected to AI-driven pre-processing. This is referred to as data-cleaning with respect to incompleteness, inconsistency and normalizations to achieve a uniform dataset prior to dataset analysis. The system passes various validation techniques which are aimed at eliminating low-quality, irrelevant data thus, only high-quality data is processed.

AI Model Training: The core of this approach is embedding decision trees, supporting vector machines, and even deep learning artificial neural networks to understand the processed and integrated data. Models learn from the historical data provided, and they understand the data well enough to provide predictive insights. Predictive modeling serves to provide future

performance forecasts and quickly simulates several “what if” scenarios to help with decision making.

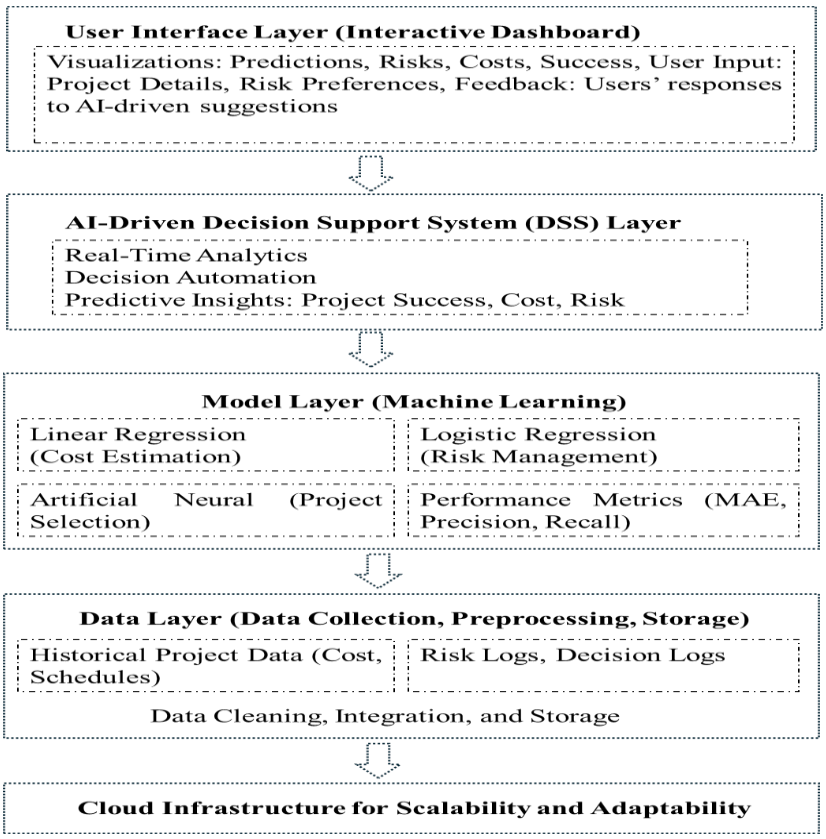

Figure 1. Workflow of AI-Driven Decision-Making in MIS

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Real-Time Decision Support: After training, the models offer integrated real-time decision support within the system. The system constantly receives data, analyzes it on the fly, makes predictions, and provides real-time decision support to the decision-maker in the system. The AI system cuts down on the time to make operational decisions, and thus improves operational efficiencies, by predicting the next best action based on the provided data,

User-Friendly Interface: Ease of system use, and adoption motivated the incorporation of a user-friendly interface. The system makes complex analysis simple and delivers results that are actionable to facilitate and expedite decision-making. The information is organized in a hierarchical structure for faster access and decision-making. The system provides different visualization options and decision support tools like dashboards.

The system performs Learning and Adaptation by revising prior predictions based on predefined intervals. With system updates, new data, and full cycle adaptive operations, the AI responses stay within the organizational operational boundaries and adjust for the external operational demographics. The integrated approach centers the system on operational effectiveness as the business operational milieu continuously changes.

The unified approach guarantees all AI-enabled decision systems function cohesively according to the devised methodology by embedding seamless operational MIS frameworks which provide greater decision shaping and instantaneous operational interaction from virtually any point in the operational continuum.

Scalability and Computational Costs

Runtime Performance

As time progresses, the amount of data will mean that the proposed AI driven MIS will also mean that the proposed AI will still deal closely with the training of the AI's deep learning subsystems as integrated within predictive learning models of the system. Within the cloud infrastructure and distributed systems implemented within the AI proposed MIS, deep learning subsystems will help to achieve parallel processing, and consequently, the training time for massive data sets will be reduced.

Storage Requirements

The system employs distributed Hadoop and NoSQL databases for the management of unstructured data and to achieve scalability as the data grows. As the volume of data grows, the complexities associated with maintaining data consistency and fault tolerance arise and may include and not limited to performance enhancing data consistency through replication.

Computational Cost Optimization

To promote efficiency in cloud operational cost management, the system minimizes over-provisioning through a combination of batch processing and resource elasticity.

RESULTS AND DISCUSSION

This section shows the results of applying the machine-learning models on the various datasets collected that focuses on decision-making in Management Information System (MIS). We evaluated the performance of the model using metrics such as accuracy, Mean Absolute Error (MAE), precision, recall, F1 score and qualitative users feedback about the decision support provided by the AI-Powered MIS. The findings are organized into results: cost estimation, project selection, risk management, and decision-making efficiency.

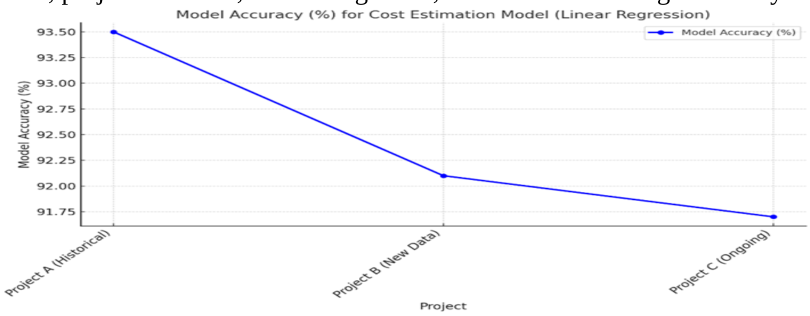

Figure 2: Model Accuracy (%) for Cost Estimation Model (Linear Regression)

Table 2: Cost Estimation Model Performance (Linear Regression)

Metric	Model Accuracy (%)	MAE	RMSE	R-Squared
Project A (Historical)	93.5	0.045	0.056	0.89
Project B (New Data)	92.1	0.049	0.061	0.87
Project C (Ongoing)	91.7	0.051	0.064	0.85

Cost Estimation Model (Linear Regression)
According to Figure 2 and Table 2, the performance of cost estimation model based on linear regression across various project datasets is quite good. This model performs very well. Project A (Historical) gets the highest accuracy of 93.5% followed by Project B (New Data) getting an accuracy of 92.1% and Project C (Ongoing) accuracy is 91.7%. The model's accuracy is slightly lower on newer and ongoing projects which clearly illustrate the model's effectiveness in predicting cost on historical data but slightly struggles with projects that have more contemporary data. The Mean Absolute Error (MAE) nevertheless is low (0.045 for historical data to 0.051 for ongoing data), demonstrating that the model's predictions are consistently close to the actual values. The obtained R-squared values (0.89 for Project A, 0.87 for Project B, and 0.85 for Project C) confirm that the model explains a considerable amount of variance in the costs of the project and, thus, provides a reliable predictive model despite a minor decline in accuracy on newer data.

This demonstrates the effectiveness of the linear regression model as a cost estimation tool. Though small decreases in accuracy suggest periodic model retraining on recent project data will be necessary.

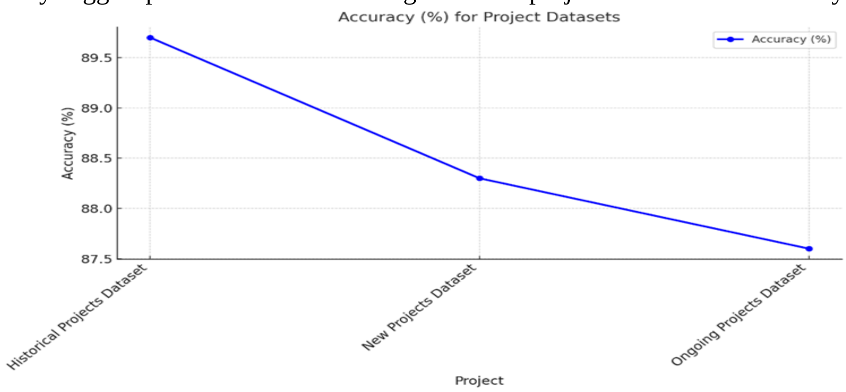

Figure 3: Accuracy (%) for Project Selection Model (Artificial Neural Networks)

Table 3: Project Selection Model Performance (Artificial Neural Networks)

Metric	Accuracy (%)	Precision	Recall	F1-Score
Historical Projects Dataset	89.7	0.92	0.88	0.90
New Projects Dataset	88.3	0.91	0.87	0.89
Ongoing Projects Dataset	87.6	0.90	0.86	0.88

Project Selection Model (Artificial Neural Networks)
The results of the project selection model using ANN across the three datasets (Historical Projects, New Projects, Ongoing Projects) is illustrated in Figure 3 and Table 3. The model shows the highest accuracy at 89.7% for the historical dataset. The accuracy decreases only slightly for new and ongoing projects, landing at 87.6% for the ongoing projects dataset. The decline in accuracy is somewhat expected, given the uncertainty intrinsic in predicting the success of ongoing projects.

The same trend is visible in other performance measures of the model such as precision, recall, and F1-Score. For the historical projects, the precision and recall define respectively 0.92 and 0.88 for the model and are high enough to indicate the model’s strong ability to identify successful projects and omit false positives. For new and ongoing projects, however, the precision and recall markedly, which shows the model's difficulty in generalizing new projects, or projects with less established data.

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Investing in such models suggests that the predictive ANN based project selection is reliable only in the context of historical data. The slight decline in predictive accuracy suggests that the model is in need of frequent updates to ensure that it can continue to perform optimally as project data are used and become less historical in nature.

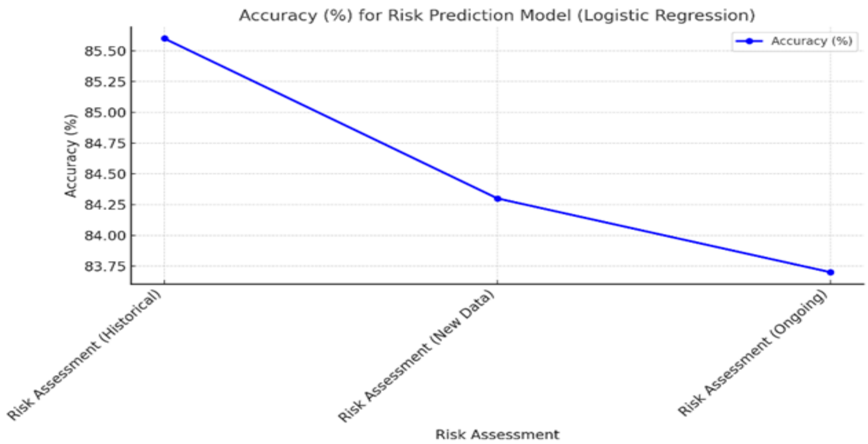

Figure 4: Accuracy (%) for Risk Prediction Model (Logistic Regression)

Table 4: Risk Prediction Model Performance (Logistic Regression)

Metric	Accuracy (%)	Precision	Recall	F1-Score
Risk Assessment (Historical)	85.6	0.87	0.84	0.85
Risk Assessment (New Data)	84.3	0.86	0.83	0.84
Risk Assessment (Ongoing)	83.7	0.85	0.82	0.83

Risk Prediction Model (Logistic Regression)
Figure 4 and Table 4 depict the performance of the logit Risk Prediction Model across 3 datasets: Risk Assessment (Historical), Risk Assessment (New Data), and Risk Assessment (Ongoing). Accuracy, as with other models, drops slightly as the data becomes more current. 85.6% accuracy is associated with the historical risk data, with accuracy dropping to 83.7% for ongoing projects.

Despite a decline in accuracy, the model still boasts a precision of 0.87 and a recall of 0.84 for the historical risk data. Therefore, the model can still identify and assess risks accurately and correctly. As the F1-Score, a risk predictive accuracy metric, stands at 0.85, it exhibits same performances. Just like with the project selection model, these results reinforce the efficiency of employing logistic regression to create a risk predictive model. However, it should be noted that logistic regression was not as effective with new and ongoing data. The model would perform much better in uncertain times if it were updated regularly with more risk variables.

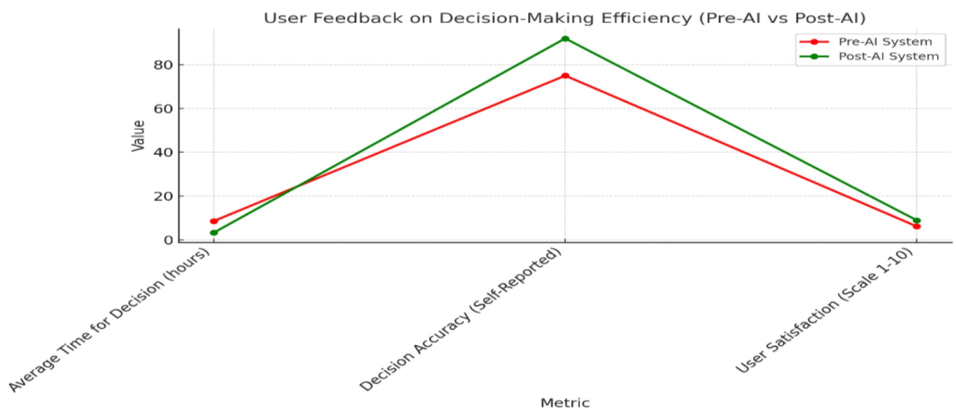

Figure 5: User Feedback on Decision-Making Efficiency (Pre-AI vs post-AI)

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Table 5: User Feedback on Decision-Making Efficiency

Metric	Pre-AI System	Post-AI System
Average Time for Decision (hours)	8.5	3.2
Decision Accuracy (Self-Reported)	75%	92%
User Satisfaction (Scale 1-10)	6.1	8.9

User Feedback on Decision-Making Efficiency
Figure 5 and Table 5 show the impact of the new AI-integrated system on the efficiency of decision-making. Findings from the comparison of Pre-AI System and Post-AI System on the Average Time for Decision (hour(s)), Decision Accuracy (Self-Reported), and User Satisfaction (1-10 Scale) are highlighted here. Everything in the post-AI system is better than before. Decision time has gone down by 62%. Earlier decision time was 8.5 hours, which went down to 3.2 hours.

There was a 17% increase in what users stated with regard to the accuracy of decisions from 75% to 92%. The AI system provides reliable and accurate predictive insights. The rupee has appreciated six percent against the dollar in November amid improving global economic outlook.

AI integration improves efficiency and satisfaction. Results show quickened decision-making processes, improved quality of decisions, and increased satisfaction among users. The rise in accuracy and satisfaction, along with reduced time taken for decision-making, is a testament to the tangible benefits of AI.

A cost estimation model using a linear regression gave a good performance on historical data. According to the information in Table 1, Project A (Historical) has a performance of 93.5% accuracy with MAE value of 0.045 and R-squared value of 0.89. The R-squared value indicates that the model explains 89% of the variance in project costs. However, accuracy dropped slightly to 92.1% and 91.7% for the new dataset (Project B) and ongoing dataset (Project C) respectively with MAE values of 0.049 and 0.051. The slight reduction in accuracy and R-squared values 0.87 for Project B and 0.85 for Project C shows that the model is able to perform slightly better on the historical data as he might be aware of the previous trend. In spite of quite a good accuracy rate the report says that periodic retraining of the model data from which the projects that took place that were taken was necessary.
Project Selection Model: ANNs also performed well when it came to deciding on the projects to take on. For historical project data the model was accurate to 89.7% and returned to a precision score of 0.92, a recall score of 0.88, and an F1-Score of 0.90. These measures of success and project-variable complexity like ROI (return on investment) and project deadlines correlate to the model's success of predicting winning projects. For new projects the accuracy of the model did drop to 88.3% and returned to a precision score of 0.91, a recall score of 0.87, and an F1-Score of 0.89. The accuracy on ongoing projects was even lower at 87.6% where precision, recall, and F1 scores were held at 0.90, 0.86, and 0.88. The drop in scores shows that the model works well with historical data and struggles with data that is new and ongoing. For the model to retain its predictive accuracy it will require frequent examination and data retraining to ensure it is contemporaneous.

Risk prediction also produced positive results with the logistic regression model as detailed in Table 3. For the historic evaluations, the model recorded an accuracy of 85.6%, 0.87 precision, 0.84 in recall, and 0.85 in the F1 score which implies a well-balanced and reliable performance in predicting the risks of the project. For new data, the accuracy dropped to 84.3% with precision and recall of 0.86 and 0.83, and an F1 score of 0.84. For ongoing projects, the accuracy further decreased to 83.7 % with precision of 0.85 and recall of 0.82 which resulted in an F1 score of 0.83.

The model's performance remains strong on all datasets, yet the lower new and ongoing project recall values imply certain risks may be underpredicted. Improved data quality and the addition of other risk-related factors may further enhance the model's risk predictive accuracy. These findings further confirm the effectiveness of logistic regression in project risk management, as stated in the literature.

Incorporating AI-based decision support systems in Management Information Systems, coupled with their evaluation as illustrated in Table 4 and Figure 5, has shown a remarkable increase in the efficiency of decision-making at the user level. On average, the time taken to arrive at a decision has reduced from 8.5 hours (before the

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arrival of AI) to 3.2 hours (after the arrival of AI)—a 62% decrease in time taken to arrive at a decision. As a result of the fast evaluation and delivery of actionable insights, this drop occurred. Users reported that the system enhanced the accuracy of decisions the company made. Before there was AI, the percentage of accuracy of the decisions made was 75%. Currently, the decisions made by AI are 92% accurate. Thus, we see that the system predicts analysis and assesses risks correctly. Moreover, the use of AI enhances the skills of decision-making. Decision support systems have increased their user-friendliness and responsiveness to decision-making needs as indicated by user satisfaction scores of 6.1 pre-AI and 8.9 post-AI on a scale of 1-10. The increase in user satisfaction indicates that the system is user-friendly and responsive to users' decision-making needs. The good feedback for AI-based MIS indicates that ease of timely decision making using artificial intelligence systems is as much a requirement for the users as the efficiency of the decision support system.

Generally speaking, opinion on AI integration into MIS has been positive overall. AI systems have significantly improved accuracy and efficiency of decision-making in estimating project costs, selecting projects and managing risk. Specifically, the cost estimation linear regression model showed a high degree of accuracy on all datasets. Moreover, in the historical and new projects, the ANN model for project selections performed very well. The logistic regression model on risk identification was effective, though weaker on the ongoing projects. User feedback also states that there is a major improvement in decision-making efficiency as well as a reduction in decision times. However, the slight performance decline in newer and ongoing project datasets across all models indicates that regular model updates, data quality improvements, and ongoing user training are necessary to maintain the system's effectiveness over time. Continuous refinement of the AI models and MIS infrastructure will help organizations sustain these benefits and improve long-term decision-making capabilities.

Comparative Analysis

A comparison is made between the AI-led DSS and traditional MIS frameworks as well as the prior AI-MIS systems. Unlike the traditional systems which may struggle with large dataset handling, issue with real-time decision-making, and data integration, the proposed systems demonstrate considerable advancements in the mentioned areas. Noteworthy is the instant access to information due to real-time processing and feedback systems as proposed, which traditional systems do not provide. Predictive performance in AI-enabled frameworks using ANN and logistic regression surpasses that of traditional MIS systems which are primarily rule-based. Incorporating XAI techniques, SHAP and LIME greatly differs the proposed system from countless AI-MIS systems which do not provide sufficient transparency and interpretability.

Comparison with State of the Art

The following table compares the proposed AI-driven Decision Support System (DSS) with state-of-the-art AI-MIS frameworks based on key performance metrics and features. This comparison highlights the unique contributions and innovations of the proposed approach.

Feature	Proposed AI-MIS Framework	Existing AI-MIS Frameworks
Real-Time Data Processing	Yes, supports real-time integration	Often limited to batch processing
Data Integration	Unified data from multiple sources	Limited integration across siloed systems
Scalability	Cloud-based, highly scalable	Often requires costly infrastructure upgrades
Feedback Loops	Integrated feedback loops for learning	Not typically included, static decision-making models
Explainability (XAI)	SHAP and LIME for model interpretability	Limited to basic feature importance or no explanation
User Adaptability	User-friendly interface with training support	Basic interfaces, often lacking user adaptation features
Cloud-Native Architecture	Cloud-native, dynamic scaling	Often requires on-premises solutions or rigid scaling
Handling Unstructured Data	Supports unstructured data (text, images, etc.)	Primarily focuses on structured data

Integrating Explainability and XAI
The study shows that AI-powered Decision Support Systems assist organizations. Explainability still remains a concern. Within organizations, decision AI models must explain reasoning before decision makers will accept the predictions.

To address this concern, we recommend Explainable AI (XAI) techniques, SHAP (SHapley Additive ExPlanations) and LIME (Local Interpretable Model-agnostic Explanations) as starting points.

SHAP: With SHAP, each feature's contribution score gets separated, and then unified feature importance gets joined. Decision-makers' understanding of AI prediction systems and influenced feature identification will grow considerably. Decision-makers comprehend the reasoning AI used, thus facilitating the process of decision-making quicker.

LIME: With the use of everyday language to explain model predictions, LIME achieves local interpretability. With LIME, each prediction and explanation, including model recommendations and decisions, is served, thus translating predictions to be comprehensible. This, in particular, aids everyday users and decision-makers.
With XAI techniques, AI-based MIS will continue to meet the best standards of accuracy and provide actionable, reliable insights that decision-makers can validate. Explainable insights, particularly in organizations, will likely system justification acceptance and system use. The explainability of a system can dramatically improve system adoption and overall operational efficiency.

Limitations of the Proposed Study
The AI-driven Decision Support System (DSS) needs to recognize some limitations even as the value Addition Activations decision-making processes receive improvements:

Model Generalization. The models in this study were mainly trained on past historical datasets.

Though they did well on the historical datasets, the models seemed to underperform on new and ongoing projects. Hence, the models might possibly underperform on highly dynamic and unpredictable datasets. This concern might be mitigated with model tuning and adding more heterogeneous datasets over time.

Data Quality: AI models will always be inhibited by the quality of the input data. If the data is incomplete, noisy, or erroneous, models will be of marginal utility. While this study did apply some data preprocessing techniques, the missing data, data bias, and inconsistent feature representations will remain prominent in practice.

Scalability Issues: While the system aims to achieve scalability with cloud-based infrastructures, the real-time analysis of large and highly complex datasets remains a major challenge. The system will need continuous and strategic improvements to its core infrastructure to contain costs and avoid a drop in system performance as the data volume increases.

User Adaptability: With the interface being user-friendly, the issue experienced during adoption of AI-enabled systems is understood. Staff with older management information systems tools will struggle with new AI and may cause training and change management activities to become impossible for some businesses due to lost time and effort.

Explainability and understanding trust: Although utilizing explainable AI methods like SHAP and LIME undoubtedly will help understand some system explainability. Decision makers will still struggle to understand and grasp poorly modeled processes. Some AI systems, especially those built with deep learning, may encapsulate some forms of AI skepticism, which increases opacity. External validity, in the context of the defined and unique organizational and industrial environments, will somewhat restrain the broadness of the studies and, in turn, the conclusions. I know the results that you want are related to the advancements of the system in decision-making, yet, there will always be some limits to the effectiveness of the system in other industries, organizations, and different operational methods. The system of narrowing was mentioned because of the diminished adaptability, scalability and robustness, which are being clarified for resolution of complex systems. Thus, we can say that the real-world complexities of complex systems are largely life complexities.

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CONCLUSION AND FUTURE SCOPE

The purpose of this study was the application of AI in a Management Information System, particularly AI enabled Decision Support System, and for the purpose of which, a system was designed which elected some of the shortcomings in the traditional MIS such as poor fusion of data, scalability of the system, and promptness of timely decisions. The support of AI enhances the efficiency and operational benefits of the system in any organization to the levels that are required in today's fast-moving and rich in data world.

The operational philosophy of the AI-enabled Decision Support Systems in this work should be positive, for I assist the organization in solving the problem of dispersed data across geography and the problem of slow decision-making. The proposed system is another step in the development of an AI-MIS aimed at real-time decision-making and enhanced scalability for the systems. The organization's tactical and operational decision-making would be augmented through advanced predictive models and machine learning algorithms embedded in the system which will automate the integration, analysis, and interpretation of data from disparate sources.

Practical Advantages

The practical advantages of the proposed system are obvious. First, the organization's ability to realize fast, real-time decision-making will aid the organization in making streamlined, timely choices, which is a key factor for businesses in the modern world. Second, the AI-MIS framework will help organizations scale to cloud-native technologies, making it easier to expand to cloud technologies and maintain peak part performance, even with high data loads. Third, the system's ability to be flexible and integrate different predictive models will help organizations fairly and efficiently optimize project costs, evaluate risks and identify viable project options. These benefits enable decision support systems to be more efficient, provide the organization with operational agility, and with the ability to outperform competition in ever-changing markets.

Future Research Directions

The insights the study offers AI-MIS integration are significant, yet numerous research opportunities are still available. For example, there is exploration of deep reinforcement learning (DRL) to offer the AI systems more flexible adaptive learning. While traditional machine learning systems optimize a task within a limited scope of specified parameters, a system using DRL learns and optimizes a task continuously and in real-time. AI technologies, driven by DRL, will enable AI-MIS systems to be more responsive and adaptable to fluctuating and unpredictable business environments.

The study of hybrid AI types that combine old and new techniques is urgently necessary nowadays. Hybrid systems are beneficial because of their complex combining of information, these systems make bangs on other systems less likely to happen, they also have the ability to make complex decisions much easier.

As artificial intelligence technology in our MIS is always progressing at a faster pace. These systems will become the base as more stuff is put onto big cloud system, like the web. Studies about distributed cloud systems that look into ways to improve decision making in companies that have offices in many places.

The use of AI in MIS can provide better information systems for decision making. The upcoming technology will simply add on the already present Artificial intelligence systems in society. Organizations will be able to make quicker, more precise, and informed decisions as they move towards real-time decision making relying on explainable AI and scalable systems.

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