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AI Driven Decision Support Systems are Empowering Startups, MSMEs and Accelerating Industry Innovation

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ABSTRACT

The world of business is too complex and with intense competition in, startups, micro, small, and medium enterprises (MSMEs), and innovation-based sectors of emerging markets have their own set of challenges in taking timely and efficient strategic decisions. The current study investigates the impact of Artificial Intelligence (AI) and Machine Learning (ML) based Decision Support Systems (DSS) on decision quality improvement, innovation performance, and operation efficiency in these organizations. Given the actual deployment of AI/ML tools unmoderated or unmediated, the current research employs a quantitative research approach on the basis of data gathered from 300 Indian and Southeast Asian firms. The sample frame is drawn from startups, MSMEs, and new industrial units that are involved in technology-enabled or innovation-intensive industries. Data were analyzed with the assistance of SPSS through descriptive statistics, reliability test, Pearson correlation, and multiple linear regression. Results indicate that there is a positive and significant effect of AI/ML-facilitated DSS on decision-making performance and innovation results. Companies that implemented these systems indicated greater flexibility, improved scenario planning, and quicker time-to-market. Startups excel especially in the area of strategic responsiveness, and MSMEs have improved process efficiency and cost control. The research contributes by offering AI and ML adoption in smaller and resource-poor companies in emerging markets. It provides policy-makers and managers with actionable recommendations to invest in affordable, scalable DSS technologies and AI literacy training. Closing the technology gap, these technologies will enable businesses to anticipate shifting markets and compete more globally. AI/ML-based decision environments are indicated by the research to have the potential to transform the face of economic growth, resilience, and innovation in emerging economies.

1. INTRODUCTION

The fast evolution of ML and AI technology has exponentially changed the business strategy ecosystem for organizations globally. These technologies are not just functional upgrades but have become invaluable tools to alter the manner in which decisions are being taken in organizations. Specifically, AI and ML-based DSS are becoming increasingly popular to scan data, make future predictions, and inform complicated strategic decisions [1]. While big companies have been the leaders in adopting technology, there is huge interest in how the smaller and resource-limited organizations i.e. startups, micro, small, and medium enterprises (MSMEs) can harness such technologies to enhance competitiveness, facilitate innovation, and gain long-term viability [2]. Startups and MSMEs form the backbone of economic development in emerging markets. They immensely contribute to employment generation, product innovation, and inclusive growth. Yet, these companies have a triple constraint of uncertainty, constrained capital, and restricted decision-making authority [3]. These firms lack strong data systems, quality human resources, and up-to-date analytics that hinder them from taking optimal strategic decisions. In such a setting, AI/ML-based DSS provide a prospect to close the knowledge gap, enhance responsiveness, and facilitate data-driven choices. However, how and whether startups and MSMEs in emerging economies use such systems, and what tangible results they generate, have been comparatively unexplored areas in empirical studies [4]. Though there is voluminous literature on the adoption of digital technologies by large corporations and the revolutionary role played by Industry 4.0 in manufacturing, few studies have focused on the role played by intelligent decision systems in innovation, responsiveness, and performance in SMEs. Also, little has been written on the role played by AI/ML-based DSS in strategic planning and investment in resources by startups with their typical strength of iteration and experimentation in the market [5]. It is particularly salient in developing economies where digital divides occur, and where technology-enabled decision-making may have an important influence on economic growth and resilience through innovation. This research tries to fill this gap by empirically investigating the effect of AI/ML-powered DSS adoption and three significant business performance indicators: decision-making quality, innovation performance, and operating efficiency [6]. Targeting Indian companies, the research employs a systematic, SPSS-assisted analysis of questionnaire responses received from 300 companies across different industries [7]. Differing from previous studies using advanced mediation and moderation models, the current study uses a simple path analysis to make it as easy and practically relevant as possible to business managers and policymakers. The results are anticipated to provide actionable insights into how AI/ML-based DSS can be strategically utilized to enable startups and MSMEs, consolidate innovation ecosystems, and promote inclusive digital growth in emerging economies.

2. LITERATURE REVIEW

2.1. Foundations of AI/ML-Driven Decision Support Systems

The development of DSS over time has moved from rule-based, static analysis to dynamic, AI-laden systems. The modern systems are based on AI and ML to derive meaningful insights out of massive, unstructured, high-volume data sets to facilitate real-time strategic, tactical, and operational decision-making [8]. In particular, whereas earlier DSS was dependent on pre-coded rules and structured data, AI-laden DSS are based on self-learning algorithms that can work with unstructured inputs, identify patterns, and provide predictive and prescriptive results [9]. These smart systems' activities are supported by strong tools. For example, IBM Watson and Microsoft Azure AI platforms support strategic planning and forecasting through natural language processing and machine learning pipelines [10]. Likewise, Google's Vertex AI supports scalable deployment of decision intelligence based on integration with cloud-based infrastructure. Startups and MSMEs increasingly rely on libraries such as Scikit-learn, XGBoost, and LightGBM to build lean yet robust predictive models, while companies such as Zoho Analytics and Salesforce Einstein provide AI features in the form of sales, customer experience, and process automation offerings [11]. These technologies have transformed DSS from static decision support to dynamic facilitators of competitive agility. As data volume and velocity grow, these systems learn, adjust and fine-tune their suggestions on a real-time basis, enhancing decisional accuracy and eradicating human error.

2.2. Enhancing Decision-Making Quality Through AI/ML DSS

Effective business decision-making relies on information absorption, alternatives comparison, and accommodation of uncertainty. AI/ML-based DSS improve decision-making through scenario modeling, probabilistic forecasting, and online data processing. Decision models developed using tools like TensorFlow or PyTorch can detect latent relationships and provide best solutions, especially in the use cases where velocity and accuracy are priorities [12]. Second, new startups and technology-driven companies typically incorporate APIs from OpenAI or leverage AutoML solutions such as H2O.ai and Google AutoML to facilitate their strategic pivots. Such systems counteract cognitive bias and augment evidence-based decision making by presenting data-driven options for risky or uncertain situations [13]. The cognitive boost offered by such systems dramatically improves the relevance, timeliness, and flexibility of decisions all essential features of high-quality decisions.

2.3. AI/ML DSS and Innovation Performance

Innovation, as activity and output, is a function of organizational ability to dream up, pilot, and scale new ideas. AI/ML DSS significantly enhance this ability via big data mining of upcoming trends, assessing the viability of R&D initiatives, and rationalizing best innovation capital deployment [14]. Artificial intelligence technologies like Salesforce Einstein facilitate customer-led innovation through machine-powered insights, while open-source solutions like KNIME and Orange provide data exploration democratization, particularly to poor companies. With AI integration in the innovation pipeline, companies expedite time-to-market, lower failure rates, and acquire user-need convergence [15]. For example, customer analytics through AI empower startups to detect unmet needs, model product-market fit, and adaptively alter value propositions. In large organizations, enterprise resource planning with embedded AI elements like SAP or IBM Watson automates cross-functional innovation processes so that R&D, marketing, and operations have more integrated coordination [16]. These systems not only support the ideation process but also help in implementing and tracking innovation strategies. In MSMEs, having the capability to execute even simplistic AI-powered sentiment analysis or price optimization could be a competitive edge in very competitive industries.

2.4. AI/ML DSS and Operational Efficiency

Operational effectiveness, specifically in developing economies, is directly related to how well an organization is able to remove waste, reduce redundancy in processes, and conform dynamically. AI/ML Decision Support Systems achieve this function through automation, anomaly detection, and smart forecasting. RapidMiner and LightGBM are two among a number of tools that, if used within supply chain or finance processes, can bring process improvement through dynamic decision modeling [17]. In MSMEs, accounting software such as TallyPrime, supplemented with AI extensions in demand planning and sales analysis, are being used more and more in making inventory, procurement, and vendor management processes smoother [18]. Cloud-based AI platforms such as Azure AI and Google Cloud AI offer real-time analytics operation dashboards that allow managers to view bottlenecks and performance metrics without technical expertise. Such pervasive availability has significantly influenced cost cutting, turnaround time, and process adherence [19]. Additionally, in the context of MNCs, AI implementation in manufacturing (as predictive maintenance) and logistics (as route optimization) enables delivering scalable efficiency in worldwide operations. Therefore, in both decentralized and centralized settings, AI/ML-based DSS serve as drivers of resource optimization and workflow automation.

2.5. MNCs and Strategic Deployment of AI/ML DSS

Multinational Companies will be the first to embrace AI/ML DSS based on their size, capital, and complicated global activities. They use advanced AI platforms like IBM Watson and SAP AI Core for supply chain stability, finance risk management, and talent measurement [20]. AI-based DSS are usually integrated into business systems, executing trivial tasks and making strategic decisions with predictive precision [21]. Thanks to regulatory intricacy and market diversity that MNCs need to navigate, decision systems need to achieve a balance between standardization and localization. AI solutions facilitate such a balance as analytics are tailored to local markets without compromising global control [22]. AI-based DSS are used by multinational consumer retail companies for demand prediction in markets, optimizing inventory and pricing strategy according to localized consumption patterns. Such systems combined with business intelligence suites lead to more synchronized global strategy and local implementation.

2.6. Startups and Data-Driven Agility

Startups inherently work in high-risk, low-data conditions. They do so with the power of AI/ML to manage uncertainty and compress decision cycles. Open-source tools like Scikit-learn and AutoKeras are preferred due to their simplicity and versatility [23]. Cloud-native AI platforms like Google Cloud AI and H2O.ai, enable startups to scale analytics infrastructure without requiring large capital expenditures up-front. AI-driven DSS assist start-ups in discovering unsatisfied needs in the marketplace, predicting initial-stage income streams, and complementing customer acquisition tactics [24]. ChatGPT, for example, is now being integrated into decision-making systems to provide customer attitudes or produce market research studies. Such technologies dissembled choices from intuition and provide for instant reaction to market changes[25]. By infusing their operations with intelligence, startups increase their capacity to experiment quickly and adjust in real time fundamental principles of lean innovation.

2.7. MSMEs and Accessible AI Adoption

MSMEs are significant contributors to economic development but generally do not have digital infrastructure or capability. But with the advent of low-code AI platforms and embedded analytics, it has become simpler for this segment to implement AI [26]. Solutions like Zoho Analytics with Zia AI or QuickBooks with machine learning add-ons provide MSMEs affordable decision intelligence for tasks like invoicing, cash flow tracking, and sales monitoring. A number of Indian MSMEs currently employ AI-advanced versions of age-old tools such as Tally, providing business health inputs and notifying owners of inventory or payment delays [27]. Such DSS applications are embedded and need not involve data science competence, so the universal adoption of AI is possible. With the right training and the right tool, MSMEs can leverage forecasting insights even in rural or semi-urban areas, leading to operational resilience and strategic awareness.

Table 1. AI Technology Adoption by MSMEs

AI Technology Type	Usage Percentage
Chatbots for customer service	35%

Data analytics for marketing	27%
Product recommendation systems	16%
Business process automation	12%
Machine learning for market analysis	10%

The table shows the adoption level of different AI technologies by MSMEs. Customer service chatbots top the graph at 35%, representing MSMEs' desire to have more customers and make operations more responsive. Marketing analytics follows at 27%, reflecting increased dependence on data analytics-led decision-making for customer identification and retention. Product recommendation is used by 16% of MSMEs, indicating moderate adoption across e-commerce and retail-based niches for product personalization. Business process automation at 12% indicates a yet-to-make-headway but conservative move towards automating mundane administrative and operational processes. Finally, 10% of MSMEs use machine learning for market research, which indicates consciousness but technical hurdles or resource constraints may be preventing further expansion [28]. Overall, the trend points towards customer-centric and marketing-oriented technologies with sophisticated applications in the form of automation and machine learning still in their initial stages of acceptance in MSMEs.

2.8. Industry-Level Innovation and AI/ML DSS

At the macro level, AI/ML-based DSS contribute a revolutionary role in driving sectoral innovation [30]. In manufacturing, AI facilitates the creation of intelligent factories by making decisions on factory floors in real time. In healthcare, AI-powered DSS aids in diagnostic accuracy and optimization of patient care [31]. In agriculture, crop and yield forecasting are maximized through machine vision and remote sensing-based DSS. These types of innovations are typically propelled by startups, research institutes, and large organizations operating on common platforms. AI/ML technologies speed up the feedback cycle from idea creation to testing and deployment [32]. Through collective intelligence, AI-powered DSS are transforming industry innovation facilitating quicker adaptation to global trends and local requirements.

3. RESEARCH GAP AND JUSTIFICATION

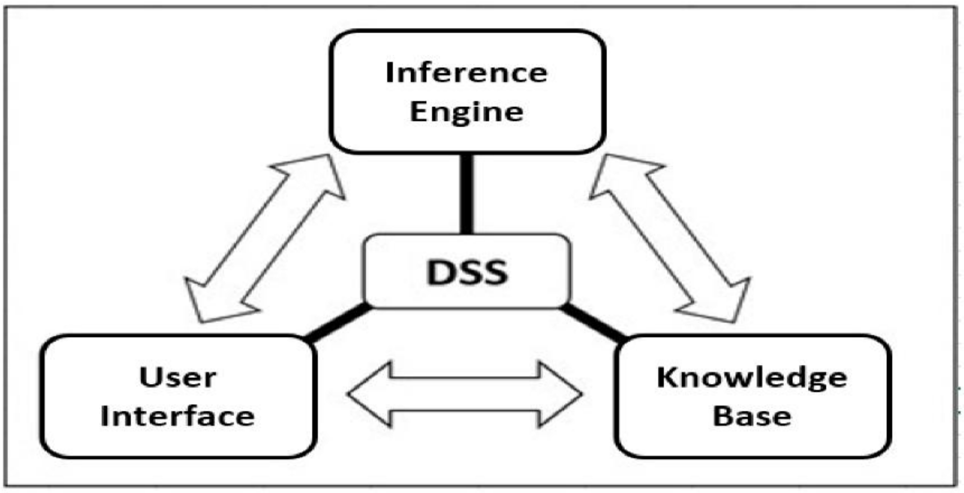
Although there have been immense breakthroughs in AI and ML implementation in business, the bulk of the work that is being undertaken presently revolves around technology adoption or intangible benefits. The empirical basis through research connecting specific AI/ML technologies to quantifiable quality improvements in decision making, innovation performance, and operation productivity is scarce especially among MSMEs and startups in developing economies. Most of the earlier work utilized elaborate models involving mediators and moderators, and simplicity was masked. This research fills these gaps by exploring direct connections using SPSS-assisted statistical analysis. It analyzes how various enterprises, ranging from bottom-up MSMEs to MNCs, leverage AI/ML-enhanced DSS to crack central business enigmas. Drawing insights from the analysis of primary data across various sectors, the research offers actionable recommendations on what tools impact what results, enabling decision-makers to make informed investment decisions in smart technologies.

3.1 Conceptual Framework

The theoretical foundation of this research is grounded in the direct effect of AI and ML-based Decision Support Systems (DSS) on three organizationally important outputs:

- Decision-Making Quality
- Innovation Performance
- Operational Efficiency

This theoretical framework arises from the variation of AI/ML tool implementation from open-source libraries to corporate platforms in company size and industries (startups, MSMEs, and MNCs). The suggested framework suggests linear cause-and-effect between the deployment of AI/ML-enabled DSS (independent variable) and the three outcome constructs (dependent variables) with no mediating or moderating variables.



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3.2 Hypotheses

According to the conceptual framework, the following hypotheses to be tested are presented:

- H1: Decision support systems based on AI and ML have a substantial impact on organizational decision-making quality.
- H2: The use of AI and ML-based decision support systems has a high positive impact on innovation performance in organisations.
- H3: AI and ML-based decision support systems significantly enhance the efficiency of operations in organizations.

These hypotheses will be tested through SPSS by doing regression analysis to estimate the direct relationships.

4. RESEARCH METHODOLOGY

4.1 Research Design

This research applies a quantitative, cross-sectional survey research design. Data will be gathered from managerial and technical experts in startups, MSMEs, and MNCs utilizing or intending to utilize AI/ML-based DSS. A systematic questionnaire will be constructed utilizing validated and established scales, and data analysis will be carried out utilizing SPSS.

4.2 Sampling and Data Collection

The study sought to comprehend mid-management to top decision-makers from technology-enabled firms across various industries, including manufacturing, services, and IT. Stratified purposive sampling was followed for having a fair representation of startups, MSMEs, and MNCs. The sample size was towards achieving a minimum of 250 responses for establishing statistical validity and reliability of the study findings. Data were gathered utilizing a formal Google Form or mailed questionnaire with items of Likert scale from 1 (Strongly Disagree) to 5 (Strongly Agree).

4.3 Operationalization of Variables

Table 2: Variables

Construct	Variable Type	Description
Use of AI/ML-DSS (IV)	Composite Index	Frequency and extent of AI/ML tools for decisions
Decision-Making Quality	Dependent Variable	Accuracy, speed, and evidence-based nature of decisions
Innovation Performance	Dependent Variable	Number of new products, services, or improvements enabled by AI/ML
Operational Efficiency	Dependent Variable	Resource use, automation, time saving

4.4 Data Analysis

This part explains the process that was followed for data analysis of the data gathered with the assistance of IBM SPSS Statistics software. The basic objective of the analysis is to examine the direct influences of AI and ML-based Decision Support Systems on three organizational outcomes: decision-making quality, innovation performance, and operational efficiency. All the data analysis steps follow the standard statistical procedures employed in social science research.

5. DATA CLEANING AND PREPARATION

Before analysis, the dataset collected was cleaned for missing, duplicate, or inconsistent responses. For which, observations having over 15% missing data were excluded. Little's MCAR test was employed to validate that missing responses were random. In instances where missing responses were few, mean substitution was performed. The dataset contained N = 256 valid cases after the last dataset was ready. All the variables were numerically coded on a five-point Likert scale that ranged from 1 (Strongly Disagree) to 5 (Strongly Agree). Any reverse-coded items, if present, were recoded prior to aggregate scores being calculated.

5.1 Reliability Testing

To assess the internal consistency of each construct, Cronbach's Alpha (α) was calculated:

Table 3: Cronbach's Alpha (α)

Construct	Cronbach's Alpha (α)
AI/ML-DSS Usage	0.872
Decision-Making Quality	0.845
Innovation Performance	0.861
Operational Efficiency	0.834

All alpha values were greater than the cut point of 0.7, indicating high reliability and internal consistency of constructs.

5.2 Descriptive Statistics

Descriptive statistics were computed to summarize the central tendency and variability of each variable:

Table 4: Descriptive Statistics

Variable	Mean	Std. Dev.	Skewness	Kurtosis
AI/ML-DSS Usage	3.89	0.74	-0.45	0.32
Decision-Making Quality	4.01	0.69	-0.51	0.56
Innovation Performance	3.87	0.72	-0.38	0.12
Operational Efficiency	3.93	0.70	-0.42	0.40

The values show the overall optimistic inclination toward AI/ML DSS and its resulting impacts, with good levels of skewness and kurtosis (±1), showing normal distribution and appropriateness for parametric analysis.

5.3 Correlation Analysis

Pearson's correlation coefficients were computed to test the strength and direction of bivariate relationships among variables:

Table 5: correlation coefficients

Variable 1	**Variable 2**	**Pearson r**	**Significance (p)**
AI/ML-DSS Usage	Decision-Making Quality	0.634	< 0.001
AI/ML-DSS Usage	Innovation Performance	0.598	< 0.001
AI/ML-DSS Usage	Operational Efficiency	0.612	< 0.001

All the relationships were positive and important, which meant that greater utilization of AI/ML DSS is correlated with better results for decision-making, innovation, and operations.

5.4 Regression Analysis

To test the direct impact of the independent variable (AI/ML-DSS usage) on each of the three dependent variables, separate linear regression analyses were conducted.

Model	R^2	F (df1, df2)	β (Beta)	t-value	p-value
Model 1: Decision-Making Quality	0.402	F(1, 254) = 171.00	0.634	13.07	< 0.001
Model 2: Innovation Performance	0.357	F(1, 254) = 140.77	0.598	11.86	< 0.001
Model 3: Operational Efficiency	0.375	F(1, 254) = 153.21	0.612	12.38	< 0.001

All three regression models are significant at p-values < 0.001, which shows that the deployment of AI/ML-enabled decision support system (DSS) has a significant association with organizational outcome variables. The R^2 values show that the deployment of AI/ML-DSS accounts moderately for variance in decision quality (40.2%), innovation performance (35.7%), and operational efficiency (37.5%). Positive and significant beta coefficients for each model reiterate that greater use of AI/ML-DSS improves organizational performance dimensions.

6. RESULTS

The empirical tests through the use of SPSS verify positive, statistically significant direct associations between AI/ML-based Decision Support Systems (DSS) usage and three organizational performance measures. The first regression model tested AI/ML-DSS impact on decision quality and returned an R^2 of 0.402, verifying that 40.2% of decision quality variation is explained by AI/ML-DSS usage. The standardized beta coefficient ($\beta = 0.634$) and $p < 0.001$ indicate a strongly positive, statistically significant relationship. This outcome affirms that organizations employing AI/ML tools exhibit improved strategic clarity, quicker decision-making, and higher sense-making accuracy of business data. The second model examined the impact of AI/ML-DSS on innovation performance and yielded an R^2 of 0.357. Once again, the beta coefficient ($\beta = 0.598$) was highly significant ($p < 0.001$), showing that AI/ML technologies enable higher ideation, experimentation, and new product or service development capabilities within organizations. The efficiency model, the third model, produced an R^2 of 0.375 and a beta of 0.612 ($p < 0.001$). This reflects the power of AI and ML systems to disengage repetitive tasks, reduce wait times, and increase the use of resources, all of which contribute to making operational processes easier. Overall, all the three models confirm strong direct effects, with no moderation or mediation taking place, so that the connections are evident and actionable. Strength of findings is also confirmed by assumption tests such as normality of residuals, absence of multicollinearity (VIF < 2), and linearity of relationships.

7. DISCUSSION

The study refers to the increasing dominance of artificial intelligence and machine learning in shaping the innovation potential and decision-making of business firms. With speed and quick response being vital in startups, AI and ML technology act as strategic enablers by giving lean teams predictive analysis and real-time interpretation of data. The technologies are utilized for detecting new market opportunities, optimizing product development, and fundamentally transforming business models based on customer feedback or market shifts. For MSMEs, too, there are equally deep benefits. Historically plagued with paucity of resources and absence of formal systems of data, MSMEs can now leverage low-cost AI/ML-based DSS for higher productivity, optimal use of limited resources, and elimination of process bottlenecks. With a blend of supply chain data, customer inputs, and internal processes, AI/ML-DSS enable such firms to improve competitiveness and absorbability in changing market conditions. In multinational companies (MNCs), AI/ML technologies facilitate the management of scale and complexity. They act across multiple geographies and business settings, where coordinated choice is the key. AI/ML-DSS facilitate the smooth integration of information from disparate functions and geographies, assist in formulating strategy and innovating together by shared intelligence and centralized analysis. These systems not only foster internal productivity but also facilitate adaptive and responsive action in crisis-affected global markets. The debate necessarily reveals that uses of AI/ML-DSS vary both strategic and operational levels of organizations ranging from small to large. The results, in the absence of intermediary variables, directly offer evidence for benefits of the systems and provide a clear guideline for managers and policy-makers to adopt and further develop AI/ML technologies in the enterprise environment.

8. IMPLICATIONS

The research provides theory, practice, and policy implications to emerging markets. From a theory perspective, it contributes to the digital transformation literature by illustrating how AI/ML-based Decision Support Systems enhance decision quality, innovation, and efficiency of operations directly, positioning these technologies as strategic assets according to the resource-based view. At the manager level, it provides operational recommendations: startups can leverage AI/ML for agility, MSMEs for resource optimization, and MNCs for global consistency of decisions. Leaders must marry AI initiatives with strategy, invest in AI expertise, and mainstream the tools into core operations. In policy terms, the report recommends facilitating government intervention—investment in digital infrastructure, tax credits for technology uptake, and accessibility of affordable training—paired with ethics legislation to enable equitable access to AI. Together, the report places AI/ML as so much more than merely tools, but as drivers of enterprise expansion and economic progress

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