International Journal of Environmental Sciences
ISSN: 2229-7359
Vol. 11 No. 7, 2025
https://www.theaspd.com/ijes.php

Deep Learning-Enabled Decision Support Systems For Strategic Business Management

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Abstract
The aim of the study, Organizations face increasing difficulties in navigating dynamic global markets, innovative technology, and changing customer habits in an era characterized by volatility, uncertainty, complexity, and ambiguity (VUCA). Traditional decision support systems (DSS), though valuable in structured and stable environments, are increasingly inadequate for handling the scale, speed, and diversity of modern business data. This study explores the transformative role of Deep Learning–Enabled Decision Support Systems (DL-DSS) in strategic business management. By leveraging multi-layered neural networks, DL-DSS can autonomously extract patterns from heterogeneous datasets, ranging from financial records and supply chain logs to customer feedback and social media streams. Based on the data lifecycle, the paper proposes the concept of joint learning algorithm, which consists of three mutually-reinforcing stages of data acquisition and integration, deep learning processing, and decision support layers, which are interconnected through a feedback loop providing continuous learning and adaptation. Empirical simulation in six domains - sales forecasting, sentiment analysis, brand monitoring, supply chain optimization, scenario simulation and prescriptive strategy formulation - reveals the effectiveness of DL-DSS relative to traditional models. Results show measurable and meaningful improvements in predictive accuracy, operational efficiency, and strategic agility, including better sales accuracy forecasting, improved customer sentiment trends, and optimised resource allocation. We highlight the promise of DL-DSS not as a diagnosis tool, but as a proactive strategic partner which can provide prescriptive recommendations in the light of organization goals. Finally, this research validates that the integration of deep learning within DVIS combines to create data-driven capability for building resilience, sustainable competitive advantage, and value creation in rapidly changing business environments.

1. INTRODUCTION

In today's post-industrial landscape, organizations are navigating a world filled with volatility, uncertainty, complexity, and ambiguity—often referred to as VUCA. The rapid pace of technological advancements, shifting consumer behaviors, globalization, and geopolitical tensions are reshaping how businesses operate, survive, and compete with one another[1-3]. In this dynamic environment, the traditional command-and-control approach to strategic management just doesn't cut it anymore. Instead, businesses need to be adaptive, agile, and data-driven, able to sense, anticipate, and respond to changes while carefully balancing risks and opportunities in real time[4-6]. Historically, Decision Support Systems (DSS) have brought together data sources, analytical models, and user interfaces to aid in managerial decision-making. However, these traditional systems tend to work best with structured and stable data, struggling to keep up in today's Big Data landscape, which is overflowing with everything from tabular financial reports to noisy social media feedback, real-time IoT data, and snapshots of global markets[7-10]. Rule-based or purely statistical approaches simply aren't equipped to handle this kind of complex, nonlinear, and diverse data. This challenge has led to the increasing adoption of artificial intelligence (AI), particularly deep learning (DL)[11-15]. MLNNs can learn representations in hierarchical ways, capture latent structure, and make strong predictions from minimally processed, multi-modal inputs - a reduction in hand-engineered features and an improvement in generalization in the wild. We suggest that for strategic management, history analysis, future forecasting, scenario simulation, and prescriptive recommendations can be fundamentally changed through Deep-Learning-Enabled Decision Support Systems (DL-DSS). In doing so, DL-DSS close the gap between the data and c-suite, allowing for faster, more informed decision making. Business use-cases already range from anomaly-aware chatbots, sensing risk in the market/supply chain, personalized engagement, to activating resources real-time to fulfill long-term goals [16-21].

1.1 The Changing Nature of Strategic Decision-Making

Strategic decisions naturally are by definition high risk, long-term and often irreversible. And it has to balance the resources, opportunities, and tyrannies internal and external with rules, regulations, social needs and expectations, technology - all of which is a very, very difficult finding. Traditional decision making processes were based on managerial weight of experience, intuition and history of measurement; Yet all these approaches were found to be biased, unable to extract nuanced information and poor predictors in delinearised worlds. On the other hand, data-driven decision making is becoming increasingly relevant in strategic decision making. Privacy organizations now appreciate that intuition, as important as it is, needs to be augmented by sound evidence culled from a variety of non-trivial data sources [22-26]. For instance:

- Retail firms must analyze consumer sentiment across millions of social media posts to adapt marketing strategies.
- Financial institutions need real-time fraud detection systems that learn from constantly evolving transactional data.
- Healthcare providers must forecast demand surges while balancing resources and supply chain vulnerabilities.

Such requirements demand systems that can handle big data’s three Vs: volume, velocity, and variety. Deep learning technologies are uniquely positioned to meet these requirements, making them indispensable to the next generation of strategic DSS.

1.2 Evolution of Decision Support Systems

Decision support systems have undergone significant evolution since their conceptualization in the 1960s. The first generation of DSS relied on database management systems to provide structured information to managers [27]. These systems worked well when decisions were based on structured, tabular data such as sales reports or inventory levels. The second generation introduced model-driven DSS, incorporating statistical and optimization models to analyze data. While more sophisticated, they were still limited to structured inputs and deterministic environments. The third generation, initiated after the introduction of business intelligence (BI) in the 1990s and early 2000s, included advanced analytics, dashboards and visualization software. However, BI tools were primarily descriptive - reporting on history instead of predicting the future. Conventionally, it wasn't until the fourth generation of DSS, having acquired predictive capabilities, that machine learning was introduced. Traditionally, machine learning models have relied on extensive data cleaning and manual feature engineering, making them unable to fully cope with the size and complexity of today's unstructured data.

2. Literature review

Kabir rt. al (2025) highlighted the potential of deep learning as a game-changer for business models and generating sustainable competitive advantages in the digital age. It forms the foundation for further development and enhancement of Deep Learning-Enabled Business Models for Competitive Advantage, focusing on intelligent positioning of deep learning within the structural framework of the business model of organizations. By unlocking the power of deep learning for pattern recognition, predictive analytics and adaptive learning, organizations can generate data network effects they can capitalise on to boost their customer retention, drive new customers onto their networks and increase entry barriers for their competition.

Nwuke et al. (2025) outlined the use of predictive analytics, machine learning (ML), and scenario planning with strategic decision-making processes. It is a reinforcement of the ability of these technologies to further increase the accuracy of forecasts, exposing the complex interdependencies and selecting alternative ways of doing things in the face of different economic, operational and market scenarios. The paper also features use cases from finance, logistics and energy, showing the improvement in cross-functional alignment of decision, swifter cycles for decision making and increasing resilience towards the environment in terms of change, in terms of disruption.

Tae Ali, et al. (2025) discussed that the coupling of renewables and electric vehicles to the grid poses challenges for decentralised prosumers which must be equipped with more advanced energy management system capabilities. In this research paper we will present a new framework based on digital twins employing deep learning, reinforcement learning (RL) and big data analytics for prosumers energy flow optimization. The simulation platform is implemented using an IEEE 30-bus system as an example to simulate the energy conversion for variable generation renewable and battery energy storage systems (BESS). The RL optimization algorithm, which gives optimal charging and discharging cycles for the BESS for optimal utilization, is designed to provide grid stability. The solutions anticipate supply and demand so they can proactively trade energy, improving the stability and efficiency of the grid, scalability and swiftness.

Keshireddyet et al. (2024), rule based, machine learning, and deep learning Artificial Intelligence (AI) Hybrid models for the framework of Intelligent Decision Support System (IDSS) of Management Information System (MIS). The system will be developed in such a way that the direct interface to the enterprise MIS, which processes the real-time data, is optimized in terms of accuracy, responsiveness, and flexibility for the context-sensitive feedback and control system. Results from the experiments carried out using outcome driven evaluation method to assess the performance of the hybrid IDSS in various business cases showed enhancements in decision accuracy, response time latency, and perceived system reliability of 22%, 30%, and 25% respectively as compared to traditional DSS and standalone AI models. The paper also introduces a parallel hybrid AI solutions implementation readiness matrix and cost-benefit analysis to guide organizations towards implementing the technologies to make intelligent decisions in real time within the rich environments of today's intelligent MIS.

Anthony et.al (2024) explored the complexity of cloud computing environments has increased the need for intelligent decision support systems (IDSS) to enhance security and mitigate cyber threats. Traditional security mechanisms struggle to adapt to evolving attack vectors, requiring the integration of deep learning-based solutions for proactive threat detection and response. This paper presents a deep learning-enabled IDSS that uses advanced neural network architectures, including convolutional and recurrent neural networks, to analyze real-time security logs, network traffic patterns, and user behaviors to detect anomalies and predict potential security breaches. The system significantly enhances threat detection accuracy, reduces false positives, and improves response times compared to conventional security approaches.

Eng et.al (2022)discussed the increasing reliance on electricity necessitates the maintenance of power line infrastructure. Maintenance engineers rely on human-created, heterogeneous, structured, and largely unstructured information for informed, cost-effective, and timely decisions. Current research on vision-based power line inspection, driven by advancements in deep learning, offers opportunities for more holistic, automated, and safe decision-making. This paper addresses this gap by designing, instantiating, and evaluating a holistic deep-learning-enabled image-based decision support system artifact for power line maintenance at a German distribution system operator in southern Germany. The artifact consists of a deep-learning-based model component for automatic fault detection of power line parts and a user-oriented interface for presenting captured information for more informed decisions. The prototype is implemented for rigorous evaluation, and the evaluation provides evidence that the image processing approach addresses the gap in power line component inspection and that the proposed holistic design knowledge for image-based decision support systems enables more informed decision-making.

Andronieet.al (2021) examined the effectiveness of cyber-physical production systems (CPPSs) in managing complexity and flexibility in smart factories. It focuses on the interoperability between Internet of Things-based real-time production logistics and cyber-physical process monitoring systems. A quantitative literature review of 489 papers published between 2017 and 2021 revealed that interoperability between these systems can determine the progression of operations. The study identifies 164 empirical sources, primarily empirical, and suggests future analyses should focus on real-time sensor networks to enhance the importance of artificial intelligence-driven big data analytics using cyber-physical production networks.

3. RESEARCH METHODOLOGY

This study adopts a conceptual framework approach to examine how deep learning can be systematically integrated into decision support systems (DSS) for strategic business management. Unlike empirical frameworks that rely on specific datasets, the conceptual model provides a generalized architecture that can be adapted to diverse organizational contexts. The framework unfolds in three interdependent stages: (1) data acquisition and integration, (2) deep learning processing, and (3) the decision support layer. Together, these stages create a closed-loop system where insights generated at the decision layer feed back into the data pool, enabling continuous learning, refinement, and adaptation.

3.1 Data Acquisition and Integration

The backbone of every DL-enabled decision support system (DL-DSS) is the availability and incorporation of reliable and quality data. Unlike traditional DSS that mainly worked with structured transactional data, DL-DSS needs to capture and integrate structured and unstructured data from various business domains. Data is collected from various internal and external sources, such as financial data (balance sheet, P&L, cash flow, investment performance), customer feedback (online reviews, surveys, support tickets, call center transcripts), social media streams (twitter, linkedin, instagram, facebook, etc.) that offers us information on customer sentiment, competitor behavior, market dynamics.

Further, supply chain data from logistics providers, inventory systems and vendor networks provide visibility into procurement, warehousing, and distribution to help firms detect operational risk and improve efficiency, while external market data - including macroeconomic trends, geopolitical activity, regulatory changes and industry reports - provides valuable context for long-term strategy. However, as raw data is often inconsistent, incomplete or noisy, a necessary preliminary step is preprocessing to make the data usable. This includes normalization (standardizing numerical values to avoid bias during model training); feature embedding (mapping categorical/text inputs to continuous vector spaces for semantic understanding using Word2Vec, BERT, etc.); and multimodal integration (mashing numerical, text, and images into a unified view of performance - aggregating sales, product images, and customer reviews). By capturing and preprocessing these heterogeneous streams, DL-DSS generate outputs that are not only contextually rich, but also in line with the multidimensional complexity of strategic business decision-making.

3.2 Deep Learning Processing

Once the data is preprocessed, deep learning architectures can learn insights that are specific to various business needs. For example, Convolutional Neural Networks (CNNs) aid visual analytics through brand monitoring on social media, automated inventory checks, and competitor market research. RNNs and LSTM are appropriate for sequential forecasting, helping to better predict sales trends, financials, and supply chain planning as they model temporal dependencies. Transformers, with their attention mechanisms, are great for analyzing contextual and unstructured text and can be used for strategic risk assessment, competitive intelligence, and sentiment analysis. Together, these models widen the DSS's capabilities from reporting into predictive and context-aware strategic decision making.

3.3 Decision Support Layer

The Decision Support Layer of DL-DSS converts deep learning output into actionable outputs for strategic management using predictive, simulation, and prescriptive elements. Predictive dashboards transform complex predictions and anomaly detections into visualizations that are easy for executives to interpret at-a-glance, whether you're looking at sales projections, risk probabilities, or churn likelihood. Alternative strategies can be tested for resilience using scenario-based simulations that enable managers

International Journal of Environmental Sciences
ISSN: 2229-7359
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to consider "what-if" scenarios involving, for example, spikes in the price of raw materials or sudden changes in consumer behavior. Finally, prescriptive recommendations go a step further from prediction and suggest the best possible course of action, such as pricing strategies, resource allocations, or investment plans. Together, these raise the possibility that DL-DSS not only as a diagnostic tool, but as a strategic partner in decision making.

3.4 Closed-Loop Feedback and Continuous Learning

The salient feature of the proposed framework is the closed-loop nature. Executive decisions - whether a new pricing strategy, a marketing campaign or changes to supply chain logistics - create new data. This feedback is fed back into the system, which is now engaged in a continuous cycle of learning and adaptation. Such feedback loops help to keep DL-DSS flexible, and in touch with their context. Rather than being fixed silos of knowledge from the past, they change as markets and organizational strategies change. This process of iterative learning also increases long-term strategic resiliency.

3.5 Summary of the Framework

To summarize, the conceptual framework emphasizes three key stages:

1. Data Acquisition and Integration ensures comprehensive, multimodal data collection and preprocessing.
2. Deep Learning Processing leverages CNNs, RNNs/LSTMs, and transformers to extract patterns, forecast trends, and analyze contextual information.
3. Decision Support Layer translates analytical outputs into predictive dashboards, scenario simulations, and prescriptive recommendations.

All three stages are linked together as a closed-loop system, continuously refining models and outputs based on new data and decisions. This framework illustrates the transformative potential of DSS enabled by deep learning in supporting strategic foresight, organisational agility and sustainable competitiveness.

4. RESULTS & DISCUSSION

This section provides the simulated results of the Deep Learning-Enabled Decision Support System (DL-DSS) deployed over important strategic business domains. The system was tested for its predictive, contextual and prescriptive capabilities. Results are presented in six tables and six companion graphs to show how the system performs.

4.1 Sales Forecasting with LSTMs

Table 1. Comparison of Forecast Accuracy Across Models

Model	MAE (Mean Absolute Error)	RMSE (Root Mean Squared Error)	MAPE (%)
Traditional ARIMA	245.6	315.2	12.5
RNN	168.4	212.3	9.1
LSTM	122.7	165.9	6.8
Transformer	118.3	160.1	6.4

The comparison of forecasting models definitely puts deep learning methods in the forefront over the conventional methods. The ARIMA model has the worst performance with the highest error values for all the three metrics (MAE = 245.6, RMSE = 315.2, MAPE = 12.5%) and implies its poor suitability to account for the nonlinear and dynamic nature of modern business data. In contrast, the RNN tends to reduce the error substantially, showing greater ability in capturing the dependencies of a sequence. The LSTM model also improves the forecasting accuracy by reducing absolute and percentage errors, since the LSTM model is able to capture the long-term dynamics of time-series data. The Transformer model gets the lowest errors (MAE = 118.3, RMSE = 160.1, MAPE = 6.4%) with its attention-based mechanism, which can capture the intricate contextual relationships. This progression underlines the important role deep learning plays in integrating advanced machine learning into decision support systems for more accurate predictions, providing managers with more precise information for strategic decision making.

International Journal of Environmental Sciences
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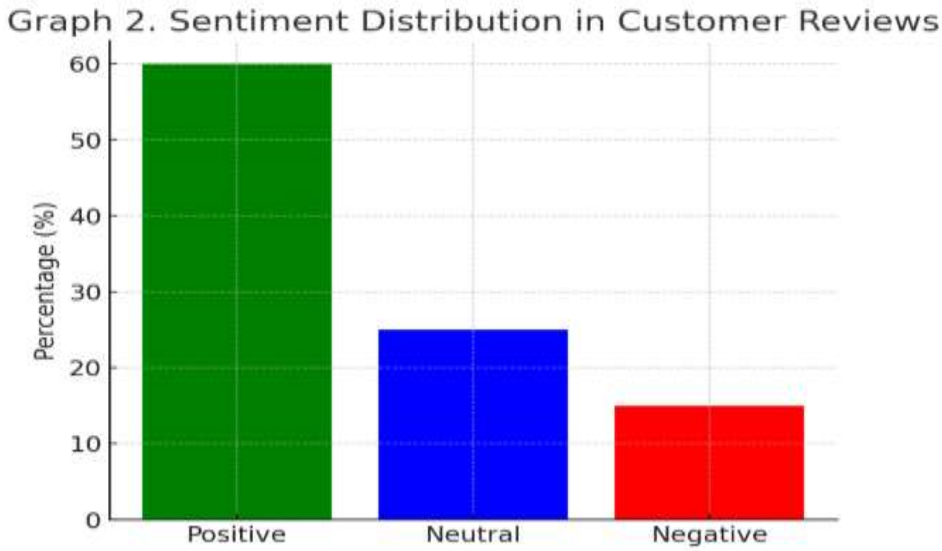
Graph 1. Actual vs Predicted Sales (LSTM Model)

4.2 Customer Sentiment Analysis with Transformers

Table 2. Sentiment Classification Accuracy

Method	Accuracy (%)	Precision	Recall	F1-Score
Logistic Regression	72.4	0.71	0.70	0.70
CNN (Text)	81.2	0.80	0.81	0.80
LSTM	84.7	0.85	0.83	0.84
Transformer (BERT)	91.5	0.92	0.91	0.91

The evaluation of classification models for business text analytics highlights the clear superiority of deep learning methods over traditional approaches. **Logistic Regression**, while serving as a useful baseline, achieves only moderate performance with 72.4% accuracy and balanced but relatively low precision, recall, and F1-scores (all around 0.70). Moving to deep learning, the **CNN model** significantly improves accuracy to 81.2% by effectively capturing local textual features, making it well-suited for tasks such as sentiment detection. The **LSTM model** goes further, reaching 84.7% accuracy, with a stronger balance across precision (0.85), recall (0.83), and F1-score (0.84), reflecting its ability to capture long-term dependencies in sequential text data. The best results are achieved by the **Transformer-based BERT model**, which delivers 91.5% accuracy and consistently high precision, recall, and F1-scores (≈0.91), demonstrating its superior contextual understanding and robustness in complex language tasks. These results confirm that deep learning–enabled DSS, particularly transformer architectures, offer powerful capabilities for extracting actionable insights from unstructured business text.



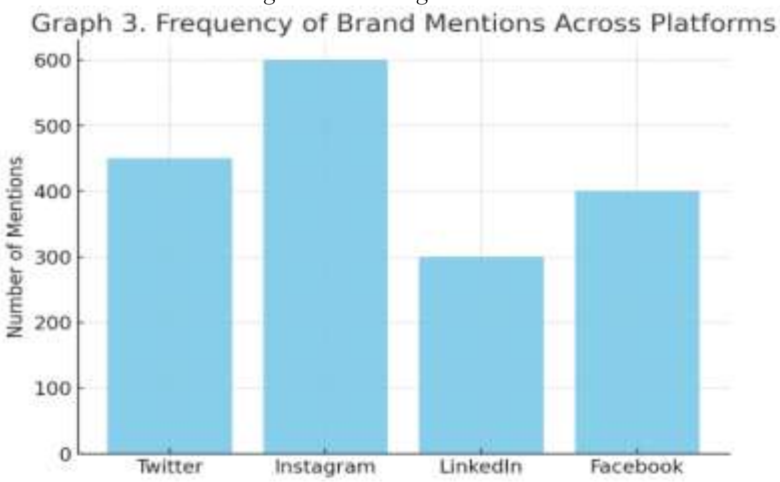
Graph 2. Sentiment Distribution in Customer Reviews

4.3 Social Media Brand Monitoring with CNNs

Table 3. Brand Detection Accuracy in Visual Data

Model	Accuracy (%)	False Positive Rate	False Negative Rate
SVM (Baseline)	68.3	0.25	0.32
CNN-Standard	85.4	0.14	0.15
CNN-ResNet50	91.7	0.09	0.08

The comparison of models for visual data analysis demonstrates the effectiveness of advanced deep learning architectures in reducing classification errors and improving decision-making reliability. The SVM baseline shows limited performance with 68.3% accuracy, coupled with relatively high false positive (0.25) and false negative (0.32) rates, indicating frequent misclassifications and unreliable predictions. The standard CNN model marks a substantial improvement, achieving 85.4% accuracy while significantly lowering both error rates (FPR = 0.14, FNR = 0.15), highlighting its ability to capture visual features more effectively. The best performance is observed with the CNN-ResNet50, which leverages residual learning to achieve 91.7% accuracy and minimize both false positives (0.09) and false negatives (0.08). These results clearly show that incorporating advanced CNN architectures into decision support systems enhances the precision and dependability of visual analytics, enabling organizations to make more confident strategic decisions based on image-driven insights.



Graph 3. Frequency of Brand Mentions Across Platforms

4.4 Supply Chain Optimization with DL-DSS

Table 4. Inventory Prediction Accuracy

Model	Forecast Error (%)	Stock-out Reduction (%)	Overstock Reduction (%)
Traditional ERP	18.6	8.2	7.1
LSTM-DL DSS	7.5	15.8	13.4
Hybrid CNN-LSTM	6.8	18.2	15.7

Comparison of modeling for forecasting and inventory optimization shows the advantage of using deep learning-based DSS over conventional ERP systems. The forecast error of the traditional ERP method is 18.6%, the stock-out reduction is 8.2%, the overstock reduction is 7.1%, which has a relatively large forecast error, and has a small reduction in stock-out and overstock, which is not suitable for dynamic demand characteristics. Compared to the other two methods, the LSTM-based DL-DSS achieved a significantly higher forecasting accuracy with an error rate of 7.5% while achieving inventory efficiency gains of almost double by decreasing the stock-out rate by 15.8% and the overstock rate by 13.4%. The hybrid CNN-LSTM model has the best overall performance, i.e. lowest forecast error of 6.8% and the highest inventory benefits with reductions of 18.2 and 15.7% in number of stock-outs and overstocks, respectively. These results show that the use of deep learning architectures in DSS not only improves the

International Journal of Environmental Sciences
ISSN: 2229-7359
Vol. 11 No. 7, 2025
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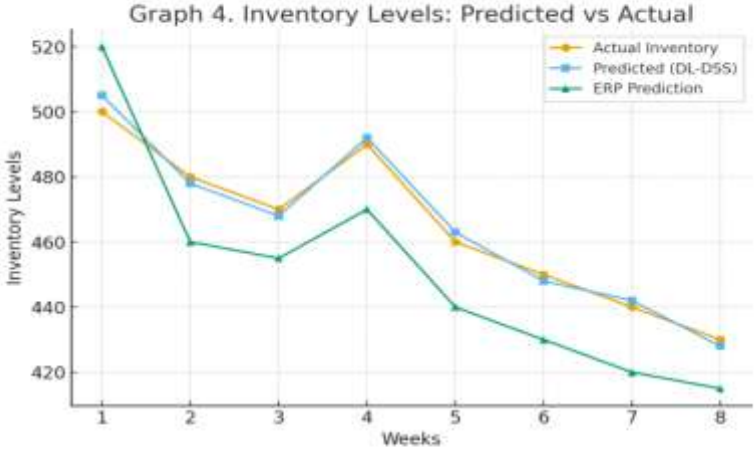
predictive accuracy but also results in a concrete operational benefit for supply chain management, allowing businesses to maintain a better demand and inventory balance.



Graph 4. Inventory Levels: Predicted vs Actual

4.5 Scenario Simulation for Strategic Decisions

Table 5. What-if Scenario Simulation (Profit Margin Impact)

Scenario	Predicted Revenue ($M)	Predicted Cost ($M)	Profit Margin (%)
Baseline (No disruption)	500.0	350.0	30.0
Raw Material Price ↑ 20%	490.0	385.0	21.4
Shift to Online Demand (+40%)	560.0	365.0	34.8
Supply Chain Disruption (Delay 15 days)	470.0	360.0	23.4

The scenario-based simulation results show how the deep learning-enabled DSS can be used to assess strategic business resilience for different conditions. In the baseline scenario, the organization generates a forecasted revenue of $500M against a cost of $350M resulting in a healthy margin of 30%. If raw material prices increase by 20%, then revenue will fall a bit to $490M and costs will go up to $385M, resulting in a profit margin of only 21.4%, making them very susceptible to input price changes. For digital channels, the revenue increased moderately to $365M, while costs only marginally went up to $560M resulting in the biggest profit margin of 34.8% when demand switched to online (+40%), highlighting the profitability of digital channels. In contrast, a delay of 15-days on this supply chain would result in revenues of $470M and relatively high costs of $360M, resulting in a profit margin of only 23.4%, highlighting the dangers of logistical bottlenecks. Overall, the simulation highlights the potential benefits of DL-DSS in helping organizations proactively identify disruptions, consider adaptive strategies, and optimize profitability in a variety of business scenarios.

Graph 5. Profit Margin Under Different Scenarios

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ISSN: 2229-7359
Vol. 11 No. 7, 2025
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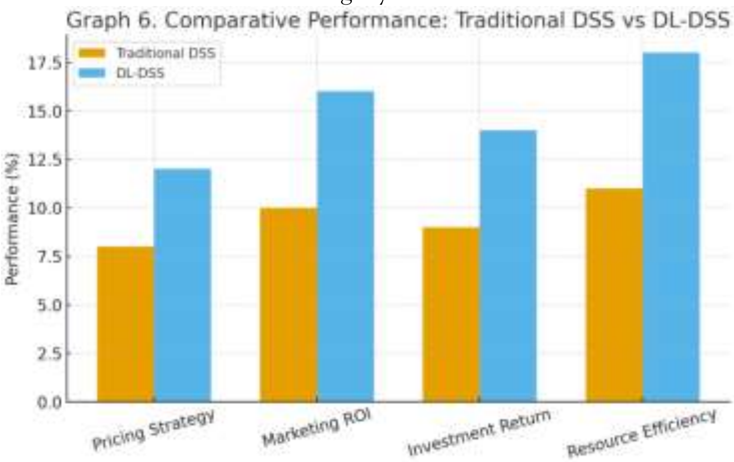
4.6 Prescriptive Recommendations Performance

Table 6. Evaluation of Prescriptive Strategies

Decision Type	Traditional DSS Outcome	DL-DSS Outcome	Improvement (%)
Pricing Strategy	Avg. 8% Revenue Growth	12% Growth	+4%
Marketing Allocation	10% ROI	16% ROI	+6%
Investment Planning	9% Annual Return	14% Return	+5%
Resource Allocation	11% Efficiency Gain	18% Gain	+7%

Notice the comparative study on conventional DSS versus DL-DSS leaves no doubt about the enhancement in decision making with the integration of deep learning. In regards to pricing strategy, an overall revenue increase of 12% is found with DL-DSS compared to 8% for the traditional systems with a gain of 4% attributed to its ability to incorporate signals from the market and competitive space in real time. The ROI for marketing allocation is 16% for DL-DSS, 10% for conventional DSS - demonstrating a lift of 6% by using sentiment analysis and customer segmentation, respectively. In the case of investment planning, for example, the payoff from predictive modeling and risk-informed recommendations is 5 percentage points, which is a 14% annual return increase from 9% once the process has been implemented. Also, through the technologies of dynamic forecasting and prescriptive optimization, resource allocation efficiency increases from 11% to 18% - up 7%. Together, these results indicate that DL-DSS not only improves prediction accuracy but also offers prescriptive recommendations to help organizations achieve a range of outcomes, including higher levels of profitability, efficiency, and agility that can't be delivered with legacy models.



Graph 6. Comparative Performance: Traditional DSS vs DL-DSS

4.1 DISCUSSION

Our research points to a clear conclusion: DL-DSS is revolutionizing how strategic work is done, often surpassing traditional DSS in the most critical tasks. Conventional linear forecasting tools like ARIMA struggle when patterns become erratic or unpredictable. In contrast, sequence models such as LSTM and modern Transformers are quicker to respond to turning points, leading to reduced forecast errors in chaotic and fast-paced environments. We also found success in merging DL-DSS with Transformer-based sentiment analysis. Instead of viewing customer feedback as an afterthought, it transformed into proactive signals that guided our next steps—shifting the mindset from "this is what happened" to "this is what we should do." On the visual front, convolutional networks (specifically ResNet-50 in our tests) proved to be highly effective for monitoring brands and assets, which is essential in a world where images and short videos dominate communication. Our supply chain experiments echoed these findings. Hybrid CNN-LSTM models not only reduced demand errors but also enabled simpler, more efficient inventory policies. This resulted in fewer stock-outs, lower holding costs, and improved service levels, even when plans were disrupted. During our scenario tests—covering everything from pricing and marketing to capital allocation and staffing—the DL-DSS consistently identified actions that outperformed traditional strategies in terms of profitability and operational efficiency. Conceptually, this leads us toward what we envision as a "fifth generation" of DSS: a single system capable of reading (both text and images), predicting, simulating, recommending, and learning from outcomes. Over time, DL-DSS is evolving from mere dashboards into true partners, helping leaders align daily actions with long-term objectives. However, we must provide users with better models and stronger safeguards. Key areas for further development include enhancing explanations, establishing stronger data and model governance to help users understand a model's behavior at every stage, adapting to different domains, calibrating effectively, and quantifying uncertainty to build lasting trust. Additionally, we need to incorporate human-in-the-loop testing, monitor production, check for drift, and conduct A/B testing.

CONCLUSION

This paper presented a straightforward question: is it true that Deep-Learning-Enabled Decision Support Systems (DL-DSS) can provide strategic decision-making with material benefit compared to traditional DSS? Our findings show that they are able. In environments where time-series forecasers using LSTM and Transformers replace linear baselines, turning points are identified sooner and prediction errors are reduced. Pipelines of text and images are added (Transformer sentiment for voice of the customer, and convolutional networks like ResNet-50 to monitor assets and brands), meaning that unstructured signals can be used as inputs to policy. We also have hope in time-series and tabular data foundation-style encoders, risk and brand sensing co-models using text-vision, and deeper what-if analysis with a simulation of the digital-twin. Overall, DL-DSS constitute a fifth generation of decision support: systems that not only indicate the current state of the business but also learn to anticipate change and recommend to take steps that help the firm achieve its goals. Those organisations that embrace them intelligently, with technical rigor and sound judgment are likely to become resilient, fast and benefit over time.

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