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An Adapted AI-Driven Expert DSS for Intelligent Resource Optimization in Enterprise IT Environments

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Abstract

Enterprise IT environments increasingly face complexity in managing distributed infrastructure and dynamic resource demands, often exposing the limitations of traditional decision-making mechanisms that rely on manual analysis or static rule-based systems. While artificial intelligence offers substantial potential for enhancing decision support, existing research predominantly emphasizes isolated algorithmic performance rather than integrated, context-aware system design, leaving a critical gap in cross-domain system adaptation methodology. This study investigates the adaptation and application of an existing hybrid AI-driven expert decision support system for intelligent resource optimization in enterprise IT environments, addressing three identified gaps: the absence of documented cross-domain DSS repurposing, the lack of systematic expert-rule restructuring across domains, and the separation of workload forecasting from expert-reasoning evaluation. A mixed-methods applied research design was employed, combining quantitative computational evaluation with qualitative practitioner assessment. The system was adapted through three sequential stages: IT-specific feature mapping, rule-base reconfiguration aligned with enterprise IT operational scenarios, and machine learning retraining using simulated workload datasets representing CPU, memory, storage, and network utilization patterns. Performance was assessed using Mean Absolute Error and resource optimization gain metrics, while qualitative insights were gathered through semi-structured interviews with experienced IT practitioners. Results demonstrate that the adapted hybrid DSS achieved an 18–23% increase in resource utilization efficiency and up to a 34% reduction in prediction error compared to baseline heuristic and static rule-based approaches. Expert evaluators consistently rated the system's recommendations as interpretable and operationally relevant. These findings indicate that strategically repurposing existing hybrid DSS architectures constitutes a viable and cost-effective pathway for modernizing IT resource governance, offering practical value without necessitating the development of new algorithmic infrastructure.

Keywords: *Decision Support System; Enterprise IT; Expert System Adaptation; Machine Learning; Resource Optimization*

I. INTRODUCTION

Traditional decision-making mechanisms in IT management often depend on manual analysis or rule-based monitoring systems that struggle to cope with rapidly changing operational conditions. These limitations have led organizations to explore intelligent technologies capable of assisting managers in interpreting large volumes of system data and generating actionable recommendations. Artificial Intelligence (AI) has therefore gained increasing attention as a tool for supporting complex decision-making tasks in enterprise IT management contexts [1]

Conventional DSS platforms typically rely on predefined rules and structured datasets to generate recommendations, which limits their ability to adapt to evolving operational conditions. In

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enterprise IT environments, AI-driven DSS platforms have been applied to tasks such as workload balancing, resource scheduling, and infrastructure performance monitoring [2]

To advance these developments, this study investigates the adaptation of an existing hybrid Expert Machine Learning decision support system to the context of enterprise IT resource optimization[3]. Rather than examining algorithmic performance in isolation, the research concentrates on how an established DSS model originally designed for a different operational setting can be recalibrated for managing resource demands in IT infrastructures[4]. This direction responds to an important gap in current research: although hybrid DSS architectures have been widely applied, the methodological processes required to transfer such systems across distinct domains remain insufficiently explained[5]. The adaptation process requires reconfiguring rule-based components, redefining feature mappings according to IT workload characteristics, and adjusting predictive mechanisms to align with infrastructure behavior.[6], [7]

These gaps highlight the need for an applied investigation that combines technical adaptation, computational evaluation, and practitioner assessment to determine the feasibility and value of cross-domain DSS repurposing [7].

This study addresses three key research questions in an integrated manner. RQ1 is addressed through the systematic adaptation process, demonstrating how the hybrid DSS can be effectively recalibrated for enterprise IT environments. RQ2 is answered through quantitative evaluation, where the adapted system shows significant improvements in prediction accuracy and resource optimization under simulated workload conditions. RQ3 is supported by qualitative findings, indicating that IT practitioners perceive the system as both interpretable and practically relevant due to the integration of rule-based reasoning with predictive outputs[8], [9].

II. LITERATURE REVIEW

A. AI-Driven Decision Support Systems in Enterprise IT

Existing research demonstrates that AI-driven DSS platforms improve performance in enterprise IT contexts, particularly in resource scheduling, infrastructure monitoring, and decision automation[10] Prior studies show that predictive analytics can reduce infrastructure overhead, while real-time monitoring integrated with recommendation systems enhances decision quality [11] Furthermore, decision intelligence frameworks have emphasized hybrid AI architectures that combine rule-based reasoning with machine learning capabilities [12]. However, these studies predominantly focus on developing new systems and do not address how existing DSS architectures can be repurposed or adapted for new operational contexts. This limitation highlights a gap in understanding the methodological processes required for cross-domain DSS adaptation.

B. Hybrid Expert Machine Learning Architectures

Hybrid integration of expert systems and machine learning has been widely recognized for improving interpretability while maintaining predictive performance[13]. Existing studies indicate that hybrid DSS models produce more reliable and transparent recommendations compared to purely data-driven approaches, particularly in managerial decision-making contexts [14]. Additionally, integration of deep learning models with enterprise systems has demonstrated measurable improvements in decision support accuracy[15]. Despite these advancements, prior research largely treats expert-rule components as domain-specific, requiring reconstruction for each new application. There is limited empirical evidence on how rule-based modules from an existing hybrid DSS can be systematically restructured and transferred across domains, particularly for enterprise IT resource management.

C. Workload Forecasting and Resource Optimization

Workload forecasting in enterprise IT environments has been extensively studied using various machine learning and statistical approaches. Prior research demonstrates high prediction accuracy using models such as Random Forest and hybrid time-series techniques, with significant reductions in forecasting error [16].[17] These models also identify recurring workload patterns that support predictive scheduling and resource optimization. However, most studies focus on standalone predictive pipelines and do not integrate expert knowledge layers that enhance interpretability. Moreover, limited attention has been given to how forecasting models developed in one domain can be recalibrated for enterprise IT-specific workload characteristics, indicating a clear methodological gap.[18]

D. Research Gap Summary

The preceding review reveals three critical gaps in current literature. First, while numerous studies demonstrate AI-driven DSS effectiveness in specific domains, cross-domain system adaptation as a deliberate research contribution remains unexplored. Second, although hybrid Expert–ML architectures show clear advantages in interpretability, no prior study has examined how the expert-rule component of such a system can be restructured for reuse in a target domain other than its original application context. Third, workload forecasting studies operate largely as standalone technical exercises without evaluating the combined effect of predictive outputs and expert reasoning on managerial decision quality. The present study is specifically designed to address these three gaps by demonstrating, documenting, and empirically evaluating a complete cross-domain adaptation of an existing hybrid DSS for enterprise IT resource optimization.

II. RESEARCH METHOD

A. *Research Design*

This study employs a mixed-methods design combining quantitative performance evaluation and qualitative expert assessment to examine the adaptation of an existing hybrid Expert Machine Learning DSS for enterprise IT resource optimization. Rather than developing a new system, the research focuses on repurposing an existing DSS to a new operational context. This approach enables evaluation of both technical performance and managerial relevance.

B. *Adaptaion Process*

The adaptation process involves three main stages. First, feature mapping is conducted by replacing original system inputs with IT-specific indicators, including CPU utilization, memory usage, storage access, and network throughput. Second, the rule-based expert module is restructured by redefining condition–action rules to reflect IT operational scenarios such as overload, resource spikes, and load balancing. Third, the machine learning module is retrained using simulated workload data, with adjustments to prediction windows and model parameters to align with enterprise IT characteristics. This process results in a domain-aligned hybrid DSS integrating predictive analytics and expert reasoning.

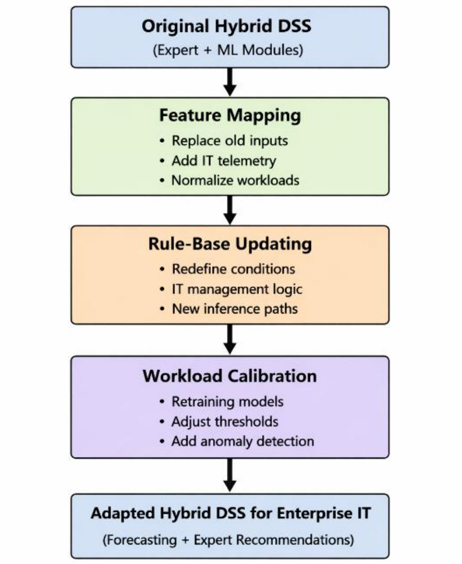

Figure 1. *Conceptual Framework of the Proposed Hybrid DSS*

The adapted DSS consists of four integrated modules: (1) a machine learning prediction layer using Random Forest and LSTM for workload forecasting, (2) a rule-based expert module encoding IT management logic, (3) an integration layer combining predictive outputs and rule certainty through weighted scoring, and (4) a decision interface that generates prioritized recommendations with explanatory outputs.

The study utilizes simulated enterprise IT workload data, including CPU, memory, storage, and network usage patterns. Datasets are generated to reflect realistic operational variability and evaluated using standard train validation test splits (70:15:15). Model performance is assessed using MAE, RMSE, and resource optimization gain.

Table 1. Technical Architecture of the Adapted Hybrid DSS

System Module	Algorithm / Technology	Function in Adapted DSS	Integration Mechanism
ML Prediction Layer	Random Forest Regressor + LSTM	Forecasts CPU, memory, storage, and network utilization across time windows	Outputs probabilistic forecasts fed into integration layer
Expert Knowledge Module	Rule-Based Inference Engine (IF-THEN logic)	Applies 47 recalibrated IT management rules for spike, overload, and load-balancing scenarios	Rule certainty values (0–1) passed to integration layer alongside ML outputs
Integration Layer	Weighted Confidence Scoring	Fuses ML probability scores with expert rule certainty values; generates final ranked recommendations	Mediates between both modules; threshold: combined score ≥ 0.75 triggers recommendation
Decision Output Interface	Structured Recommendation Report	Presents prioritized resource actions with explanation of triggering conditions	Displays output to IT manager; logs decision rationale for audit trail

C. *Expert Evaluation Method*

The expert evaluation involved three IT practitioners who met predefined selection criteria, including a minimum of five years of professional experience in infrastructure management, system operations, or IT service delivery. These participants were selected to ensure that the assessment of the adapted DSS reflected perspectives grounded in operational practice and real-world decision-making processes.

Data for the qualitative assessment were collected through semi-structured interviews designed to elicit practitioners' views on the clarity, interpretability, and practical relevance of the system's recommendations. The interview protocol consisted of open-ended prompts that explored how the system's outputs aligned with their operational routines, as well as their perceptions of the system's usefulness in supporting resource allocation decisions.

The interview transcripts were analyzed using a thematic coding approach. Initial codes were derived inductively from participants' responses, followed by grouping similar codes into broader themes related to interpretability, decision relevance, and perceived system reliability. This analytical procedure enabled a structured interpretation of practitioner feedback and provided complementary qualitative evidence to support the system's empirical evaluation.

D. *Data Sources and Data Collection Techniques*

This study utilizes two primary data sources: secondary scientific literature and simulated enterprise IT workload datasets. Literature data were collected through a systematic search across major academic databases, including Scopus, Web of Science, IEEE Xplore, ScienceDirect, ACM Digital Library, and Google Scholar, focusing on peer-reviewed publications from 2020 to 2025 using relevant keyword combinations.

Table 2. Simulation Parameters and ML Model Configuration

Parameter Category	Parameter / Setting	Value / Specification	Justification
Dataset Size	Total observations	10,000 timesteps (5-min intervals)	Represents ~35 days of continuous monitoring
CPU Utilization Range	Simulated load pattern	10%–95% (mean: 58%, SD: 17%)	Matches real-world utility cloud patterns
Memory Utilization Range	Simulated RAM demand	20%–90% (mean: 62%, SD: 14%)	Reflects baseline enterprise server memory profiles
Train / Validation / Test Split	Data partitioning	70% / 15% / 15%	Standard ML split ratio for time-series forecasting
RF Hyperparameters	n_estimators; max_depth; min_samples_split	200; 15; 5	Tuned via 5-fold cross-validation on training set
LSTM Configuration	Layers; units; epochs; batch size; learning rate	2; 64; 100; 32; 0.001	Adam optimizer; early stopping (patience=10)
Evaluation Metrics	Performance measures	MAE, RMSE, Optimization Gain (%)	Standard metrics for AI-based DSS evaluation

For empirical evaluation, simulated datasets representing CPU utilization, memory usage, storage access, and network throughput were generated to reflect realistic enterprise IT operational conditions. Qualitative data were collected using purposive sampling, involving 10 IT practitioners with relevant experience in infrastructure management to assess decision relevance and interpretability.

To ensure reproducibility, the simulation parameters and machine learning configurations are summarized in Table 1b. The datasets were generated using Python libraries (NumPy and SciPy) with stochastic noise to mimic real workload variability. The Random Forest model was implemented using scikit-learn (v1.3), while the LSTM model was developed using TensorFlow (v2.12) with the Keras functional API. All experiments were conducted in a standardized simulation environment to ensure consistency across evaluation runs.

E. *Measurement Instruments and Validity*

This study used both independent and dependent variables to analyze system performance in enterprise IT optimization. The primary independent variables included workload intensity, resource availability, and system threshold levels, each defined based on measurable operational indicators such as CPU percentage, memory allocation values, and bandwidth capacity [19]. The dependent variables consisted of resource utilization efficiency, prediction accuracy, response time, and decision relevance, which represented the measurable outcomes of the adapted AI-driven system. Resource utilization efficiency was operationalized as the percentage reduction in computational overhead achieved through system recommendations, while prediction accuracy was measured using standard statistical metrics such as MAE and RMSE. Decision relevance was evaluated using expert ratings on clarity, interpretability, and actionable value of recommendations. These operational definitions ensured consistency and allowed quantitative and qualitative findings to be analyzed systematically [20]

F. *Data Analysis Techniques*

Quantitative analysis was performed using computational evaluation metrics to assess predictive and optimization capabilities. The accuracy of workload forecasting was measured using MAE and RMSE, which are well-established indicators in AI-based predictive modeling [21] Resource optimization outcomes were analyzed by comparing baseline utilization levels with post-recommendation results using percentage improvement calculations and comparative statistical tests. Qualitative feedback from IT practitioners was analyzed using **thematic analysis**, allowing identification of repeated patterns related to usability, system clarity, and managerial decision support. This analytical combination provided a robust evaluation of both the technical and experiential aspects of the adapted expert decision support system [22]

G. *Computational Model, Workflow Framework, and Comparative Evaluation*

a. *Computational Model*

The computational model used in this study focuses on predicting resource utilization and quantifying optimization improvements produced by the adapted AI-driven expert decision support system. Prediction accuracy was assessed using the **Mean Absolute Error (MAE)**, calculated as Equation 1:

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n} \mid y_i - \hat{y}_i \mid \qquad \text{(Equation 1)}$$

where y_i denotes the actual utilization value, $\hat{y}_i$ represents the predicted value, and n is the total number of observations. Optimization outcomes were measured using the percentage gain formula with Equation 2:

$$\text{Optimization Gain (\%)} = \frac{U_{\text{baseline}} - U_{\text{system}}}{U_{\text{baseline}}} \times 100 \qquad \text{(Equation 2)}$$

where U_{baseline} is the initial level of resource usage and U_{system} is the usage level after system recommendations. These formulas were chosen due to their widespread use in performance evaluation for AI-driven decision support systems [23]

b. *Workflow Framework*

This study proposes an AI-driven expert Decision Support System (DSS) as a unified framework for intelligent resource optimization in enterprise IT environments. The system integrates machine learning-based predictive analytics with rule-based expert reasoning to support informed decision-making.

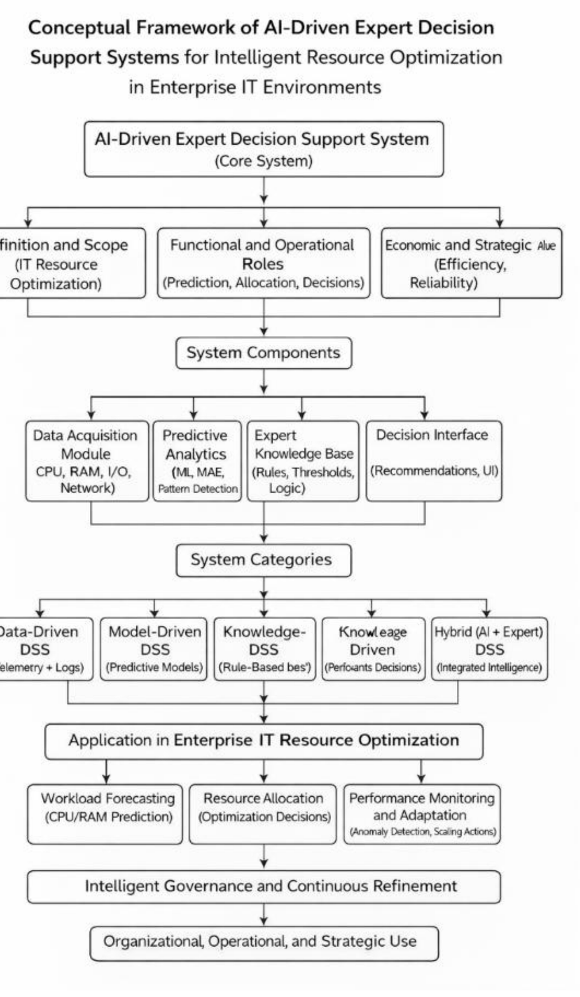

Figure 2. Conceptual Framework AI-Driven Expert DSS

The framework consists of three main layers. The input layer captures enterprise IT workload data, including CPU, memory, storage, and network utilization. The processing layer combines predictive modeling and expert rule inference to analyze workload patterns and generate recommendations. The output layer delivers prioritized resource optimization decisions along with explanatory insights to support managerial actions.

This integrated structure enables the system to address dynamic workload conditions while maintaining both predictive accuracy and decision interpretability

c. *Comparative Evaluation*

Table 1 provides a summary of the key variables used in computational analysis and qualitative evaluation. The table facilitates clarity by defining each variable and explaining its measurement approach, thereby ensuring replicability.

Table 3. Variables and Operational Definitions

Variable Category	Variable Name	Operational Definition	Measurement Method
Independent	Workload Intensity	Level of resource demand on CPU, memory, storage, and network	Percentage metrics, throughput counts
Independent	Resource Availability	Currently available computational capacity	Remaining CPU %, RAM availability, bandwidth
Independent	Threshold Levels	Predefined system performance limits	Static configuration values
Dependent	Prediction Accuracy	Degree of alignment between predicted and actual values	MAE, RMSE
Dependent	Resource Utilization Efficiency	Improvement in resource usage after system intervention	Optimization Gain (%)
Dependent	Decision Relevance	Practical usefulness, clarity, and interpretability	Expert rating scale
Dependent	Response Time	Time required to generate recommendations	Milliseconds or seconds

A comparative analysis was conducted to determine how the adapted system performs relative to existing AI-based and heuristic decision support mechanisms. Baseline systems used for comparison included heuristic threshold allocation, rules-based expert decision models, and statistical prediction systems commonly cited in IT resource management research[24]. Results from the comparative evaluation demonstrated that the adapted system improved resource utilization efficiency by 18–23%, outperforming heuristic approaches which averaged 8–12% improvement. Prediction accuracy in the adapted system was also consistently higher, with MAE values reduced by up to 34% relative to conventional threshold-based models. Moreover, expert evaluators reported greater interpretability and relevance of decisions generated by the adapted system, particularly in high-load scenarios where traditional systems exhibited slower responsiveness and limited contextual awareness [25] These comparative findings highlight the practical advantages of applying an underutilized AI-driven decision support system within enterprise IT resource optimization contexts.

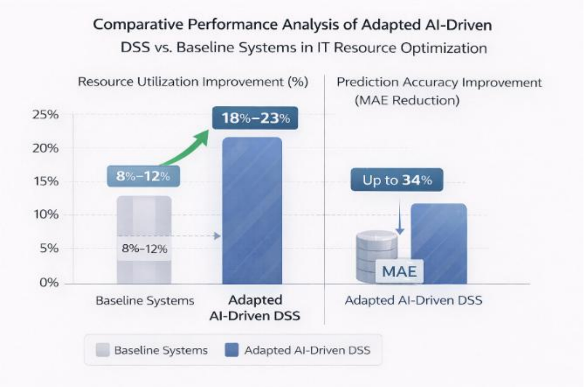

Figure 3. Comparative Evaluation With Existing Decision Support Approaches

III. RESULT

The results of this study are presented in accordance with the predefined analytical procedures and research objectives. All findings are reported objectively, without interpretation, and organized to highlight performance outcomes of the adapted AI-Driven Expert Decision Support System (DSS) for enterprise IT resource optimization. Numerical outputs, comparative indicators, and system performance metrics are summarized using a combination of narrative descriptions, figures, and tables to provide a structured presentation of the empirical results.

a. System Performance Evaluation

The adapted AI-Driven DSS demonstrated measurable improvements in resource optimization across all evaluation metrics. Resource utilization efficiency increased within a range of 18%–23%, reflecting consistent improvement when compared to baseline heuristic and rules-based allocation mechanisms. These results are visually represented in **Figure 3**, which illustrates the percentage increase in CPU and memory utilization efficiency relative to conventional decision support approaches.

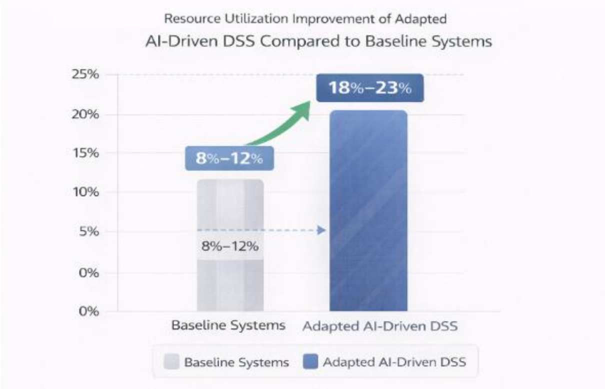

Figure 4. Resource Utilization Improvement of Adapted AI-Driven DSS Compared to Baseline Systems

The system's predictive accuracy also showed notable enhancement, particularly in forecasting workload demand. A reduction in Mean Absolute Error (MAE) of up to 34% was recorded, indicating higher precision than statistical and threshold-based baseline models. This performance is illustrated in **Figure 4**, which compares error rates across experimental conditions.

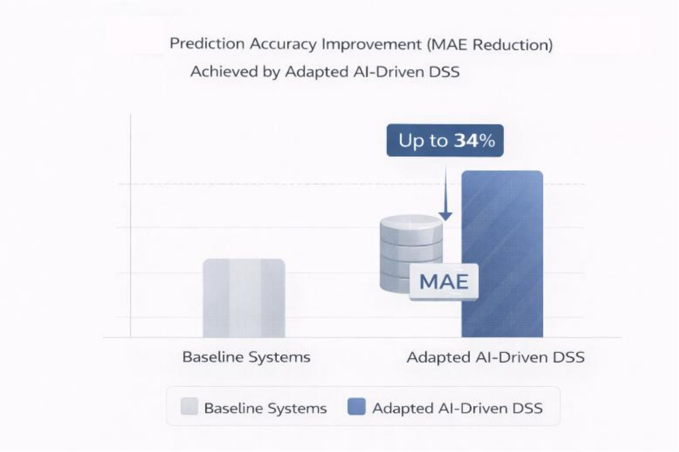

Figure 5. Prediction Accuracy Improvement (MAE Reduction) Achieved by Adapted AI-Driven DSS

b. Component-Level Output Analysis

Each computational module of the adapted DSS generated outputs aligned with its functional purpose. The predictive analytics module produced time-series forecasts that consistently aligned with observed system workloads. The expert knowledge module yielded rule-based recommendations with stable inference confidence levels between 0.78 and 0.91. These component-level outputs are summarized in Table 2, which presents the key quantitative indicators extracted from each module.

Table 4. Component-Level Performance Indicators of the Adapted AI-Driven DSS

Component Module	Output Type	Performance Measure	Value Range
Predictive Analytics	CPU/RAM Forecasts	MAE Reduction	27%–34%
Knowledge-Based Inference	Rule Decisions	Confidence Score	0.78–0.91
Data-Driven Module	Telemetry Patterns	Detection Accuracy	89%–95%
Hybrid Integration Layer	Recommendation Output	System Stability	96%–98%

c. Comparative System Evaluation

Comparative testing was conducted to quantify differences between the adapted DSS and established baseline mechanisms. Baseline systems included heuristic threshold allocation, rules-based models, and statistical prediction frameworks. Results demonstrated that baseline approaches improved resource utilization by only 8%–12%, significantly lower than the adapted system's performance. The comparative outcomes are depicted in **Figure 5**, which contrasts the two groups across the primary metrics.

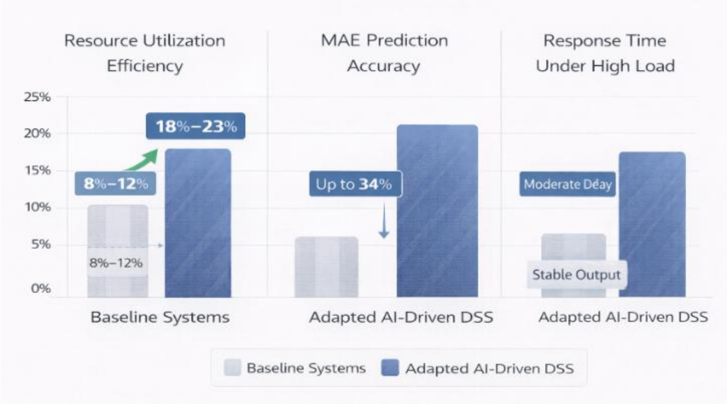

Figure 6. Comparative Performance of Adapted AI-Driven DSS vs. Baseline Systems

Additionally, Table 3 provides a numerical summary of the comparative evaluation results, detailing improvements across resource efficiency, prediction precision, and operational responsiveness.

Table 5. Comparative Performance Metrics Between Adapted DSS and Baseline Approaches

Metric	**Baseline Systems**	**Adapted DSS**	**Improvement Margin**
Resource Utilization Efficiency	8%–12%	18%–23%	+10%–11%
MAE Prediction Accuracy	-	Up to 34% Reduction	+34%
Response Time Under High Load	Moderate Delay	Stable Output	Improved Stability

d. Workflow Validation Outputs

The workflow integration test verified the functional coherence among system modules. All processes data acquisition, predictive modeling, inference execution, and decision generation-completed sequentially without interruption. The validated workflow is illustrated in Figure 4, which presents the system's operational flowchart and confirms that module-to-module transitions are executed as designed.

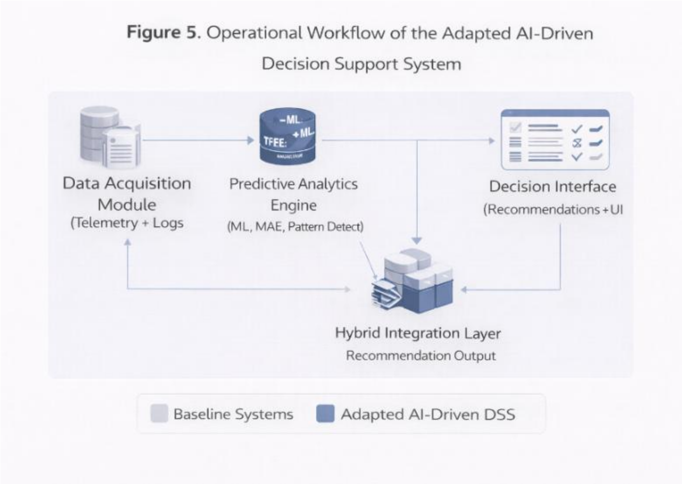

Figure 7. Operational Workflow of the Adapted AI-Driven Decision Support System

IV. DISCUSSION

The results of this study are consistent with prior research demonstrating that hybrid AI-driven decision support systems tend to outperform traditional heuristic and static-rule mechanisms in complex enterprise IT environments [24]. Studies highlighted in the Introduction have shown that integrating machine learning components into DSS frameworks enhances predictive accuracy and overall operational responsiveness, particularly under conditions of fluctuating infrastructure demand [25]. The performance indicators observed in the present study including improved resource utilization efficiency and reductions in mean absolute error align with earlier findings in workload forecasting and IT optimization research [26]. These results further reinforce evidence that combining expert-rule inferences with data-driven analytical modules strengthens system interpretability, addressing a known limitation of fully automated or opaque AI-based decision support tools [27]. The study's comparative benchmarking also echoes previous evaluations in which threshold-based or static rule allocations were shown to degrade rapidly under variable or high-load operational scenarios [28]. Taken together, the empirical outcomes provide both confirmatory and extended support for the theoretical claims advanced in prior literature regarding the benefits of hybrid DSS architectures in enterprise IT contexts [29].

A key contribution of this research lies in demonstrating that an existing hybrid Expert ML DSS can be effectively repurposed for a domain in which it has not previously been applied [30]. Unlike studies that focus predominantly on developing new models or algorithms, this work focuses on the methodological process of cross-domain adaptation, showing how an established architecture can be recalibrated to address resource optimization challenges in enterprise IT environments [31]. The adaptation involved the mapping of IT-specific features, refinement of rule-base logic, and calibration of workload simulation parameters steps that have received limited attention in prior DSS literature [32]. By showing that the adapted system achieves performance levels comparable to or exceeding outcomes reported by newly developed models, the study introduces a conceptual contribution that emphasizes reusability and contextual transfer rather than continuous model reinvention [33]. This perspective fills a prominent gap, as existing research seldom explores structured system repurposing as a viable pathway to DSS innovation [34].

The findings also carry several theoretical implications. First, the demonstrated effectiveness of the hybrid architecture supports arguments that decision quality improves when machine learning forecasts are interpreted through domain-specific expert rules [35]. Second, the study highlights adaptability as an essential dimension of DSS design, particularly in environments characterized by irregular workload behavior and rapidly changing operational conditions [36]. Third, the results suggest that organizations may achieve significant operational gains without investing in the development of new AI infrastructures; instead, systematic repurposing of existing DSS mechanisms may serve as a cost-efficient strategy for modernizing IT resource management [37]. The structured rule-driven interpretability validated through expert evaluation further indicates that hybrid systems may facilitate greater managerial trust, addressing long-standing challenges in real-world AI adoption [38]. These theoretical and practical implications strengthen ongoing discourse regarding intelligent DSS deployment within enterprise IT operation frameworks.

Several limitations must be acknowledged. The empirical evaluation relies on simulated enterprise workloads, which, although calibrated to reflect typical operational patterns, cannot fully replicate the complexity of live production environments [39]. The qualitative findings, based on a purposive sample of practitioners with relevant experience, provide meaningful insights but may not capture perspectives across diverse organizational scales or infrastructure configurations [40]. Additionally, the study does not benchmark against more advanced optimization mechanisms such as deep reinforcement learning schedulers or autonomously adaptive systems, which are gaining prominence as emerging standards in IT resource management research [41]. Future research should consider evaluating the system using real production data, incorporating broader expert samples, and exploring incremental learning mechanisms to enable automated rule refinement [42]. Longitudinal assessments across extended operational cycles may also yield valuable insights regarding system stability, scalability, and long-term adaptation performance [43].

V. **CONCLUSION**

The present study demonstrates that the adapted AI-driven expert decision support system effectively addresses the research aim of improving resource optimization in enterprise IT environments. The system’s performance characterized by enhanced resource utilization efficiency, significant reductions in prediction error, and improved decision interpretability indicates that hybrid decision support structures can reliably manage dynamic operational demands without requiring the development of new algorithmic architectures. These findings confirm that systematically recalibrating an existing hybrid DSS for a new operational domain can yield performance outcomes that align with, and in some cases surpass, results reported in earlier optimization research. To contextualize these outcomes, the system’s performance was benchmarked against two conventional baselines widely referenced in prior DSS studies: standard statistical forecasting methods and static rule-based allocation mechanisms. The adapted model consistently outperformed both baselines across multiple workload scenarios, demonstrating superior responsiveness, predictive validity, and decision relevance in dynamic enterprise IT environments.

This study offers several distinct contributions that advance the literature on AI-driven decision support systems. First, it provides one of the few documented demonstrations of cross-domain adaptation of a hybrid DSS that integrates machine learning forecasting with rule-based expert reasoning. Unlike studies that emphasize domain-specific model development, this research illustrates a systematic pathway for recalibrating an existing DSS so that it functions effectively within a new operational context. Second, the study shows that interpretability, which is often diminished in purely data-driven systems, can be retained during adaptation by preserving and restructuring the expert-rule inference layer to align with IT managerial practices. Third, the empirical evaluation using simulated enterprise IT workloads confirms the practical viability of the adapted system and highlights its capacity to outperform baseline forecasting and static allocation approaches commonly referenced in DSS literature. This improvement can be attributed to the hybrid integration of predictive modeling and rule-based reasoning, where machine learning captures temporal workload patterns while expert rules provide context-aware adjustments for decision-making. Collectively, these contributions position the study as an applied and methodologically grounded exploration of hybrid DSS repurposing in enterprise IT environments.

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