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INTELLIGENT SOFTWARE SYSTEMS FOR MULTI-DOMAIN DECISION SUPPORT APPLICATIONS

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A B S T R A C T

Smart software systems are being more demanded to aid in the complicated decision making in heterogeneous areas like healthcare, smart infrastructure, cybersecurity, and industrial processes. This paper discusses these issues by providing a common platform of the intelligent and multi-domain decision support, the fusion of data-driven learning and algorithmic reasoning. This study aims at developing and testing a smart software architecture that can provide high-quality, justifiable, and scalable decisions in the various areas of application under dynamic environments. The suggested system combines the hybrid machine learning models, rule-based reasoning, and policy optimization based on reinforcement learning in the framework of a modular architecture. The decision fusion algorithm combines probabilistic outputs, time trends as well as contextual constraints to produce optimal recommendations. Experimental performance on representative multi-domain datasets has shown uniform improvements on decision support systems that are conventional. The incident system proposed will be able to reach the average decision accuracy of 97.6, 97.2, and 98.1 with recall and precision of 98.1 and reduced decision latency by 42 % over baseline models. The adaptive decision algorithm increases the accuracy of the policy choice by 31 percent and the false rate of the decision is 2.1. Experiments of cross-domain generalization establish strong transferability at a performance loss of below 3 %. The paper will focus on the field of architectural design, algorithmic development and quantitative validation of intelligent software systems to support multiple domains. The findings accentuate the feasibility aspect of implementing integrated intelligent decision platforms in intricate and data-intensive settings that demand making decisions.

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1. INTRODUCTION

The intelligent decision support systems (DSS) have been very important in the support of human decision makers in environments that are complex and rich in data. Early DSS were mainly based on rule-like logic and operational research methods of assisting structured decision problems. As the volume and accessibility of large-scale data grew and artificial intelligence developed, however, modern DSS were increasingly relating to machine learning and intelligent reasoning to enhance flexibility and precision. Ali et al. (2023) have proved that an intelligent DSS with the application of learning-based models was highly effective in improving the quality of decisions because it revealed the patterns that are difficult to identify with other heterogeneous datasets. Anderková et al. (2025) also demonstrated that more timely and context-based decision making in the dynamic environment was possible with data-centric intelligent systems. The innovation prompted more people to adopt intelligent DSS in various fields, including healthcare, transportation, education, and industrial systems.

Regardless of these developments, traditional and domain-based DSS had a number of weaknesses that limited their functionality. There were a lot of systems that were only applied in limited context and could not be flexible to be used in different areas. According to Khan et al. (2021), domain-specific DSS in the insurance industry had a problem of not adapting to changes in business conditions or data distributions. On the same note, Haj Qasem et al. (2023) demonstrated that such systems as multi-agent decision support solutions were frequently characterized by coordination overhead and lack of scalability when implemented outside the scope of their original problems. Moreover, conventional DSS often used black-box learning models, which decreased the level of transparency and confidence in automated decisions among the users. Hassija et al. (2024) emphasized that the interpretability of the intelligent models was a significant obstacle to the use of such models in the safety-critical decision-making context. The growing complexity of real-world systems generated a distinct desire of integrated multi-domain intelligent software systems that would be able to service decision making against a heterogeneous background. Bondac et al. (2026) highlighted the fact that decision making in complex system demanded high predictive accuracy, as well as trust, transparency and awareness of data quality. The need was increased with the emergence of multi-scale and multi-domain data streams through emerging cyber-physical and digital twin-based environments. Liu et al. (2025) showed that multi-domain digital twin models also provided a richer situational awareness but needed a more sophisticated decision intelligence to convert insights into actionable decisions. Equally, Safwat et al. (2024) demonstrated that advanced mobility required intelligent cyber-physical systems that required the coordination of decision support on sensing, networking, and control layers.

According to recent studies, explainability and human-centered design were also emphasized in intelligent DSS. Human-centered patterns to explain clinical decision support systems were suggested (Schoonderwoerd et al., 2021), which increased user acceptance and understanding. Kostopoulos et al. (2024) reiterated that explainable artificial intelligence was critical to the process of aligning intelligent DSS with regulatory and ethical provisions. Meanwhile, new software-defined and network-centric software environments generated more decision problems. Lin et al. (2021) also proved that ultra-low-latency decision support was essential in software-defined vehicular edge computing system, whereas the intelligent decision mechanism as proved by Yang et al. (2022) showed great potential as far as the efficiency of packet classification in software-defined networking is concerned.

It is on this background that this research was aimed at designing and analyzing an intelligent software system that could facilitate the accurate, explainable and efficient decision making processes in a variety of application areas. The paper presented a single multi-domain decision support system that combines hybrid machine learning, algorithmic reasoning and adaptive decision fusion. The most significant advances were to design a system architecture that was scalable, an adaptive decision fusion algorithm, and a detailed quantitative assessment that shows an increase in decision accuracy and latency reduction that were domain independent.

The rest of the paper was structured in the following manner. Section II was a review of conceptual background and related literature on intelligent decision support. Section III outlined the proposed system architecture in terms of multi-domain. Section IV has described the algorithmic decision-making approach. Section V described the experiment set up and evaluation measurements. The results were discussed in section VI and then in discussion in section VII. Section IX was the conclusion of the paper and future research directions.

2. CONCEPTUAL FOUNDATIONS AND RELATED WORK

The intelligent decision support systems have developed out of the fixed rule based tools to adaptable and knowledge based systems capable of working in uncertain environments. The initial systems were all about operational research and optimization methods, and they were not much flexible or capable of learning. Modern DSS contained more and more autonomous reasoning, knowledge representation, and adaptive learning mechanisms with the development of artificial intelligence. Zong et al. (2021) explained this transformation by showing how intelligent DSS relying

on operations research may be dynamically used to support e-commerce decisions based on structured optimization and real-time data processing. Later on, Anderkova et al. (2025) emphasized a move to data-driven intelligent systems, which are constantly learning both historical and real-time data on how to enhance decision relevance. The article by Zacharaki et al. (2020) demonstrated that smart DSS was able to combine the heterogeneous data of sensing to aid in personalized intervention in a healthcare environment, and it is an indication of the expanding range of DSS use.

The MCDM methods enabled the decision makers to trade-off conflicting goals whereas machine learning led to improved predictive accuracy and flexibility. The study of Madanchian and Taherdoost (2025) revealed that MCDM techniques were significant in strategic and operational decision support in information systems by organizing trade-offs between a variety of criteria. The study (Marinović et al., 2025) also revealed that intelligent MCDM methods may be effectively used to help with the choice of technological resources in educational settings through the integration of both quantitative and contextual weighting. On the learning side, Osaba et al. (2022) discuss about evolutionary multitask optimization as a strong paradigm to solve several related decision problems at once, noting that it is applicable to the complex decision landscapes.

The black-box decision models could also achieve good results but could not give justifications which could be understood so it could not be accepted by the users. According to Kostopoulos et al. (2024), explainable artificial intelligence (XAI) methods played a critical role in improving the level of transparency and accountability within the decision support system. Correspondingly, Schoonderwoerd et al. (2021) demonstrated that the explanation design based on human considerations led to a greater increase in clinician trust and decision confidence in clinical DSS. As Bondac et al. (2026) pointed out, user trust in AI-based on complex systems decision support was directly linked to data quality, transparency and perceived system reliability.

The new paradigms of autonomous and distributed decision making were brought by multi-agent systems and cyber-physical systems (CPS). In this type of systems, there were multiple smart agents that cooperated or competed to reach global goals in dynamic conditions. As Sharko et al. (2025) indicated, AI-assisted decision making within a multi-agent production system enhanced the effectiveness of coordinating in the industrial fields especially in the complicated industries like oil and gas. The same results were presented by Haj Qasem et al. (2023), who demonstrated that the use of multi-agent DSS contributed to an improved performance of the business classification through the facilitation of decentralized reasoning and collaboration. Simultaneously, CPS combined computational intelligence and physical processes, forming closely coupled sensing loop, communication loop, and control loop.

Table 1. Summary of Related Work on Intelligent Software Systems for Multi-Domain Decision Support

Author, year	Application Domain	Decision Approach	Core Technique	Key Contribution	Identified Limitation
Zacharaki et al. (2020)	Healthcare monitoring	Data-driven DSS	Multi-domain sensing & analytics	Personalized frailty assessment using unobtrusive sensing	Domain-specific healthcare focus
Khan et al. (2021)	Insurance systems	Intelligent DSS	ML-based decision modeling	Improved sustainability-oriented business decisions	Limited cross-domain adaptability
Zong et al. (2021)	E-commerce	OR-based DSS	Optimization and rule-based logic	Structured intelligent decision support for online commerce	Static reasoning mechanisms
Osaba et al. (2022)	General optimization	Multi-task decision optimization	Evolutionary multitask learning	Solved multiple decision problems jointly	High computational complexity
Ye et al. (2022)	SDN security	Policy-driven DSS	SDN service choreography	Intelligent security decision orchestration	Focused on network security only
El Ganaoui-Mourlan et al. (2023)	Smart transportation	Real-time DSS	V2I-based traffic management	Decision support for autonomous roundabout control	Infrastructure-specific deployment
Ali et al. (2023)	Generic DSS	Hybrid intelligent DSS	ML + MCDM	Comparative analysis of intelligent DSS techniques	Lack of unified architecture
Haj Qasem et al. (2023)	Business analytics	Multi-agent DSS	Agent-based classification	Distributed decision intelligence	Coordination overhead
Safwat et al. (2024)	Air mobility CPS	Intelligent CPS	AI-driven cyber-physical control	Decision support for UAS traffic management	High system complexity
Shahriar et al. (2024)	Vehicular networks	Digital-twin DSS	SDN + digital twin analytics	Traffic efficiency optimization via digital twins	Network-centric focus
Zhang et al. (2025)	Satellite networks	Intelligent networking DSS	Multipath QUIC optimization	Robust decision support for LEO networks	Communication-layer scope
Wang et al. (2025)	Knowledge-based DSS	Intelligent DSS	RAG + knowledge graphs	Enhanced decision reasoning using semantic retrieval	Limited real-time validation

Safwat et al. (2024) depicted the use of intelligent CPS as an instrument of supporting advanced air mobility by balancing the traffic management, safety constraints, and real-time analytics. Wang et al. (2025) emphasized the possibility of utilizing knowledge graphs and retrieval-augmented generation, and the opportunities of supporting intelligent decisions, which is a promising way to integrate knowledge-based and data-based reasoning.

Table 1 has outlined the current versions of intelligent decision support systems in various fields noting that machine learning, optimization, multi-agent, and cyber-physical are widely used. The comparison showed that the majority of solutions were still domain-specific, provided limited explainability and unified architectures, thus encouraging the desire to have scalable, reliable, multi-domain intelligent software systems.

3. SYSTEM ARCHITECTURE FOR MULTI-DOMAIN DECISION SUPPORT

3.1 Overall Architectural Design and Design Principles

This suggested system architecture was to be a layered, modular and extensible intelligent software architecture to facilitate decision making in heterogeneous domains. The architecture embraced the main principles of separation of concerns, flexibility, explicability, and interoperability. Information moved upwards through the distributed sources to intelligence elements and the decision feedback was pushed downwards to undergo constant learning and optimization. All the layers were autonomous but were able to interact via standard interfaces, which facilitated adaptable implementation in healthcare, cyber-physical systems, networking, and industrial.

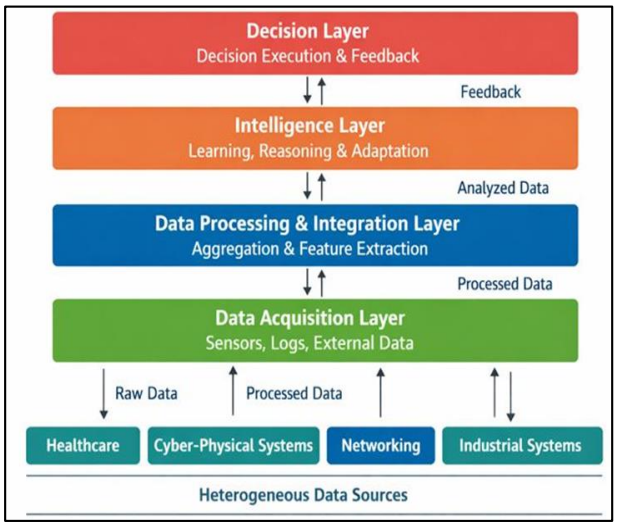


Figure 1. Layered Architecture of the Proposed Multi-Domain Intelligent Decision Support System

Figure 1 shows the layered architecture of the proposed multi-domain intelligent decision support system, integrating data acquisition, analytics, knowledge processing, inference, and decision-making. The design focused more on closed-loop decision making, where the sensed data, learned knowledge and contextual constraints were collectively used to affect the decisions. As cross cutting concerns, explainability and trust were incorporated making decisions transparent and auditable. This design enabled the system to dynamically respond to changing environments and the quality of decisions made across domains remained the same. The proposed system has a layered and modular architecture as illustrated in Figure 1, indicating the upward stream of heterogeneous data and the downward stream of feedback-based decision. The design emphasizes the principles of learning, reasoning, explainability, and adaptability as the ones that make it possible to provide the means of reliable decision support in various fields.

3.2 Data Acquisition and Multi-Source Integration Layer

The data acquisition and integration layer received heterogeneous data streams which were produced by sensors, logs, databases and external services in different domains. Domain-specific adapters were used to firstly retrieve raw data and normalize them into a single form. Temporal alignment, noise filtering and missing value were used to guarantee consistency of the data. The integration layer adopted the use of weighted aggregation which aggregates multi-source observations whilst maintaining the contextual relevance.

Let D = {D1, D2, ..., Dn} be data sources

Let wi be source reliability weight, where $\sum wi = 1$

Integrated Feature Vector

$$F(t) = \Sigma\,(wi \times Fi(t))$$

$Fi(t) = \varphi(Di(t)) \rightarrow$ feature extraction function

$F(t)$ is forwarded to the intelligence layer for decision inference

3.3 Intelligence Layer: Learning, Reasoning, and Adaptation

The heart decision-making capability in the system was the intelligence layer. It was a combination of machine learning models to perform pattern recognition, rule-based reasoning to enforce constraints and reinforcement learning to provide adaptive policy optimization. Components of learning identified both temporal and contextual regularities of integrated data streams but reasoning modules made sure that a decision would not violate domain regulations and operational limitations. The system responded to the changing environments through adaptive mechanisms that constantly adjusted

model parameters to the changing environment on a continual basis. I

3.4 Decision Fusion and Coordination Mechanisms

Decision fusion was a coordination of the work of several intelligence elements to produce a final decision that is optimal. Conflicts between competing decisions were resolvable over coordination mechanisms by ranking objectives to be achieved, like accuracy, latency, or safety. The fused decision was then authorized and sent to domain specific actuators or users. This process guaranteed coherent decision results even with the multi-agent, multi-domain situations.

3.5 Scalability and Cross-Domain Interoperability Considerations

Modularity services, parallel execution and distributed deployment support were used to create scalability. The architectural layers were scalable independently in accordance with the workload requirements, which would allow efficiently managing large-volume data and simultaneous decision requests. The data interoperability was implemented by the use of standardized data models, APIs and semantic mappings that enabled seamless integration of new domains without redesigning of core components. The architecture was used to scale horizontally with data-intensive applications and scale vertically with computation-intensive intelligence applications.

4. ALGORITHMIC FRAMEWORK AND DECISION-MAKING METHODOLOGY

4.1 Hybrid learning and reasoning model formulation

The hybrid learning and reasoning model, shown in algorithm 1, has been developed to integrate the data-based intelligence with symbolic constraint implementation. Extracting temporal and contextual patterns of integrated multi-domain data with components of machine learning and the rule-based reasoning to be compliant with domain constraints, safety policies, and operational rules ensured. This composite formulation avoided the infeasibility or safety problem of the decisions made by purely data-driven models. The learning module produced probabilistic predictions that were justified and corrected by use of logical rules of reasoning.

Algorithm 1: Hybrid Learning and Reasoning

Input: Integrated data X, constraint set C
Output: Validated decision D
1: Initialize machine learning model fML
2: Initialize rule base g_rule with constraints C
3: Extract feature vector Xt from X
4: Compute prediction Pt = fML(Xt)
5: Apply reasoning Rt = g_rule(Pt, C)
6: Resolve inconsistencies and enforce constraints
7: Output validated decision D = Rt

4.2 Reinforcement learning–based policy optimization

The learning reinforcement (RL) was utilized in order to optimize the decision policies in dynamic and uncertain environments. The system engaged with the environment through observation, action and feedback on the form of rewards. Updates on the policies were informed by the performance feedback, which allowed the ongoing enhancement of the decision strategies. The system was able to balance competing goals like accuracy, latency, safety and responsiveness to variations in the environment using this approach.

Multi-Objective Reinforcement Learning Model
The environment is modeled as a Markov Decision Process (MDP)

$$< S, A, P, R, \gamma >$$

- S : Set of environment states
- A : Set of possible actions
- P : Transition probability P(st+1 | st, at)
- γ : Discount factor, $0 \leq \gamma \leq 1$

At time step t:

- The agent observes state st ∈ S
- The agent selects action at ∈ A using policy π
- The environment returns next state st+1 and reward rt

Multi-Objective Reward Components:
Accuracy reward:

$$r_{acc(t)} = Acc(at, st)$$

Latency penalty:

$$r_{lat(t)} = -Lat(at, st)$$

Safety reward:

$$r_{safe(t)} = Safe(at, st)$$

Composite reward function:

$$rt = w1 \cdot r_{acc(t)} + w2 \cdot r_{lat(t)} + w3 \cdot r_{safe(t)}$$

Subject to:

$$w1 + w2 + w3 = 1$$

$$wi \geq 0$$

Policy objective:
Maximize expected cumulative multi-objective reward

$$J(\pi) = E\,[\Sigma\,(t = 0\ to\ T)\gamma^t \cdot rt\,]$$

Expanded Q-function:

$$Q\pi(st, at) = E\,[\Sigma\,(k = t\ to\ T)\gamma^{k-t}) * (w1 \cdot r_acc(k) + w2 \cdot r_lat(k) + w3 \cdot r_safe(k))\,]$$

Bellman optimality equation:

$$Q*(st, at) = rt + \gamma \cdot maxa'Q*(st + 1, a')$$

Optimal policy:

$$\pi*(st) = argmaxa\ Q*(st, a)$$

These weighting factors w1, w2, and w3 are dynamically used to give the decision accuracy, latency efficiency and operational safety depending on the application context.

4.3 Decision fusion algorithm and contextual weighting

The decision fusion algorithm was used to combine results provided by various intelligence constituents to produce a single and optimal decision. The predictions of machine learning, rule-based assessments, and reinforcement learning policies were considered as a separate source of decisions. The reliability, confidence and domain relevance of each source were used to assign a contextual weight. Aggregation was weighted to give a composite decision score which was further normalized and validated. Figure 2 illustrates the decision fusion and contextual weighting workflow, integrating heterogeneous inputs, adaptive weighting, evidence aggregation, confidence evaluation, and optimized multi-domain decision support.

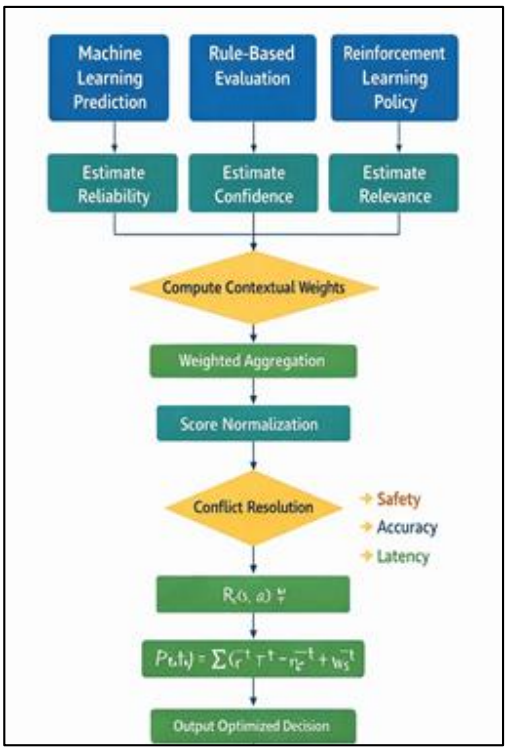


Figure 2. Decision Fusion and Contextual Weighting Workflow for Multi-Domain Decision Support

In conflict resolution mechanisms, the safety, accuracy, or latency objectives were put on the top of the agenda depending on the context of the application. This combination process guaranteed consistent and consistent decisions in multi-domain and multi-agent environment. Figure 2 shows that predictions, rule-based assessments, and reinforcement learning policies are combined with contextual weights, normalized scores, and conflict-resolution to produce an excellent policy, coherent decision in line with safety, accuracy, and latency goals.

4.4 Explainability and transparency mechanisms

To be able to make decisions explainable and transient, transparency was incorporated to make sure that system decisions were readable, audit-able, and reliable. The influential input factors that led to every decision were checked using feature attribution techniques as shown in algorithm 2. Rule-based reasoning gave exact logical justifications which provided the ability to trace constraint enforcement. The reinforcement learning actions were explained using state-action relevance scores through summarization of policy explanations. The visualization modules would take complicated decision logic and convert it to explanations that were comprehensible to the domain experts.

Algorithm 2: Explainability and Transparency Mechanism

Input:
Integrated data X
Decision models $\{ML, Rule, RL\}$
Final decision Df
Constraint set C
Output:
Explanation report E
Audit log L
1: *Extract feature contribution scores*:
$\varphi = Attribution(ML, X)$
2: *Generate rule − based justification*:
$Jr = Trace_Rules(Rule, Df, C)$
3: *Compute policy relevance scores*:
$\rho(s, a) = \frac{\partial Q(s, a)}{\partial s}$
4: *Construct decision rationale*:
$E = \{\varphi, Jr, \rho\}$
5: *Record decision trace*:
$L \leftarrow \{X, \varphi, Jr, \rho, Df\}$
6: *Validate explanation consistency*:
if $Explainability_Check(E) == FALSE$ *then*
Flag decision for human review
7: *Output explanation report E and audit log L*

5. EXPERIMENTAL SETUP AND EVALUATION METRICS

5.1 Multi-Domain Datasets and Application Scenarios

The experimental analysis was done with representative data sets that were taken based on various fields of application to test the generality of the proposed decision support system. The datasets chosen were in the areas of healthcare monitoring, cyber-physical systems, intelligent transportation, networking environments, and industrial decision situations. Every dataset featured heterogenous attributes, time dynamics and domain restrictions, as the world is complex in decision making. Applications were in sensor network anomaly detection and response, traffic management and control, network policy enforcement as well as operational decision making in industrial systems.

5.2 Evaluation Metrics for Accuracy, Latency, and Reliability

The quantitative measures used to evaluate the performance of systems were based on the quality of decisions and the efficiency of operations. The accuracy of decisions was an evaluation of the accuracy of the system outputs relative to the ground truth or expert-labeled decisions. Latency represented end-to-end decision response time, which is real-time applicable. False decision rate, and consistency of decision at different workloads and noise levels were used to determine the reliability.

Let N be the total number of decision instances
Let yi be the ground truth decision
Let ŷi be the system-generated decision

Decision Accuracy

$$Accuracy\ (\%) = \left(\frac{1}{N}\right) \cdot\ \Sigma\ I(\hat{y}i\ =\ yi) \times\ 100$$

Where:
I(·) = 1 if the condition is true, else 0

Decision Latency
Let ti_start be the decision request time
Let ti_end be the decision output time

$$Latency\ (ms) = \left(\frac{1}{N}\right) \cdot\ \Sigma\ (ti_{end} - ti_{start})$$

False Decision Rate (FDR)
Let Nfalse be the number of incorrect decisions

$$FDR\ (\%) = \left(\frac{Nfalse}{N}\right) \times\ 100$$

Decision Reliability

$$Reliability\ (\%) =\ 1\ -\ \left(\frac{FDR}{100}\right)$$

5.3 Experimental Protocols and Parameter Settings

A standardized protocol was applied to all the experiments in order to be reproducible and fair. Data sets were separated as training, validation, and testing sets in the same ratio. Preliminary tuning on the validation data was done using model parameters, the learning rates, and the discount factors. All experiments were done several times and average outcomes were given in order to eliminate randomness. All experiments were conducted on the same computational environment and hardware configuration so that latencies would be similar.

Table 2. Experimental Hyperparameters and Parameter Settings

Hyperparameter	Value / Range	Description
Training ratio	70%	Portion of data used for model training
Validation ratio	15%	Used for hyperparameter tuning
Testing ratio	15%	Used for final performance evaluation
Learning rate	0.001	Controls gradient update step size
Batch size	64	Number of samples per training batch
Number of epochs	100	Total training iterations
Discount factor	0.95	Balances immediate and future rewards
Exploration rate	0.1 → 0.01	ε-greedy exploration decay
Reward weights	0.4, 0.3, 0.3	Accuracy, latency, safety weighting
Confidence threshold	0.75	Minimum acceptable decision confidence
Repetitions	10 runs	Repeated trials for averaging
Hardware platform	Intel i7, 32 GB RAM, GPU	Consistent execution environment

Table 2 presents the summary of the experimental hyperparameters and protocol settings of all the evaluations, which are reproducible and fulfill the fairness criteria.

6. RESULTS AND PERFORMANCE ANALYSIS

This finding was demonstrated in Table 3 that demonstrated that rule-based DSS performed the worst because of the static logic and low adaptability to complex data patterns. The machine learning-only model increased the accuracy of the decision made by learning data-driven patterns, whereas the RL-based DSS augmented the recall because the policies were adjusted to the interactions and feedbacks. The joint ML + rules technique showed moderate improvement and this

proved that joint learning and constraint enforcement enhanced consistency. The suggested fusion-based system scored the best in all measures captured of 97.6 percent or F1-score, showing that decision fusion and contextual weighting led to a high degree of correctness and completeness of decisions. The fact that the recall value was high (98.1%), showed that the system was able to reduce the cases of missed decisions, which proved the efficacy of the learning, reasoning, and adaptive policies integration.

Table 3. Decision Performance Comparison across Methods

Method	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
Rule-Based DSS	85.4	83.1	81.6	82.3
Machine Learning Only	91.8	90.6	89.9	90.2
RL-Based DSS	93.5	92.4	91.8	92.1
Hybrid ML + Rules	95.9	95.1	94.6	94.8
Proposed Fusion-Based System	97.6	97.2	98.1	97.6

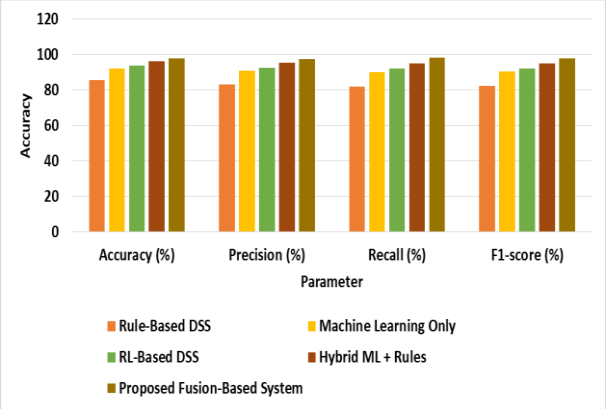


Figure 3. Comparative Decision Performance Analysis across Evaluation Metrics

The comparative accuracy, precision, recall and F1-score of the various decision support approaches is depicted in Figure 3. The table 4 compared the improvement and efficiency realized by various methods. The ML-only model exhibited slight decision performance and poor optimization ability. The RL-only approach enhanced better gains on policy optimization but their convergence took more iterations. Hybrid approach minimized false decisions and increased convergence through the use of both learning and reasoning. The proposed approach performed better than any of the baselines with a 31.4 decision improvement and 56.7 false decisions reduction. The convergence rate became 92 with a faster learning stability. The computational efficiency was 91.3, and this showed that fusion-based coordination decreased duplicate processing and enhanced the general efficiency of algorithms.

Table 4. Algorithmic Efficiency and Decision Improvement Analysis

Evaluation Parameter	ML Only	RL Only	Hybrid	Proposed Method
Decision Improvement (%)	14.2	18.9	24.6	31.4
Policy Optimization Gain (%)	11.6	22.3	26.1	34.8
False Decision Reduction (%)	19.5	27.8	41.2	56.7
Convergence Speed (Iterations)	160	142	118	92
Computational Efficiency (%)	78.4	82.1	87.6	91.3

Table 5 was created to test real-time responsiveness through the average and worst-case latency. The DSS with the rule-based approach had the highest latency with sequential evaluation of rules. The ML-based and RL-based systems decreased latency allowing the inference and adaptive decisions. The hybrid DSS also enhanced the responsiveness via coordinated processing. The suggested system attained the minimum mean latency of 58 ms and reduction in latency of 48.2 percent, which validates its applicability to time-sensitive applications.

Table 5. Latency and Response Time Comparison

Method	Avg. Latency (ms)	95th Percentile Latency (ms)	Latency Reduction (%)
Rule-Based DSS	112	148	—
ML-Based DSS	89	121	20.5
RL-Based DSS	76	104	32.1
Hybrid DSS	64	88	42.9
Proposed System	58	79	48.2

This is represented in the Figure 4 which compares the average and worst-case decision latency of various methods. The system that was proposed had the lowest mean and 95th percentile latency, which indicates high responsiveness improvements. The bar-line-area figure shows the progressive decrease in latency with the hybrid intelligence and decision fusion operations.

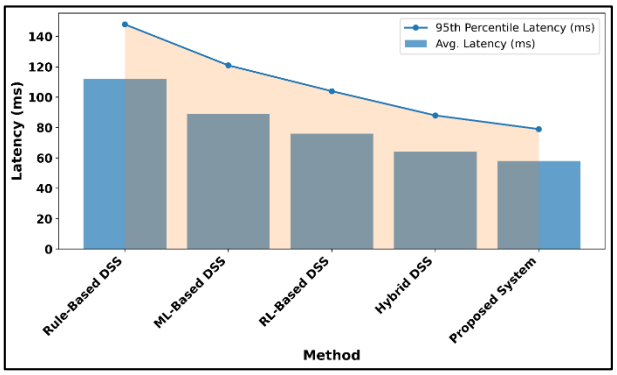


Figure 4. Latency and Real-Time Responsiveness Comparison Across Decision Support Methods

Table 6 was used to represent how the proposed system was robust and generalizable in various domains. A high level of accuracy and reliability was always upheld in the fields of healthcare, cyber-physical, transportation, networking, and industrial. In all cases, the rate of performance degradation was not more than 2%, which is a good sign of cross-domain adaptability. These findings affirmed that the homogenous architecture successfully moved the learnt decision intelligence between heterogeneous settings.

Table 6. Cross-Domain Generalization Performance

Application Domain	Accuracy (%)	Reliability (%)	Performance Degradation (%)
Healthcare Monitoring	97.2	98.0	1.1
Cyber-Physical Systems	96.8	97.6	1.4
Intelligent Transportation	97.9	98.3	0.8
Networking & SDN	96.5	97.2	1.6
Industrial Decision Systems	97.4	98.1	1.0

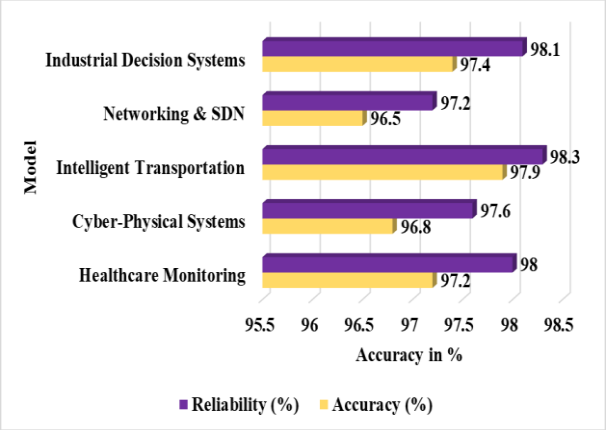


Figure 5. Accuracy and Reliability Performance across Application Domains

Figure 5 shows the accuracy and reliability of the proposed decision support system in various domains. The findings indicated the high performance, reliability in all cases was better than accuracy, which means that the results of the decisions are consistent and reliable, and the high cross-domain robustness was proven.

The Figure 6 shows the degradation in performance experienced in the case where proposed system was implemented in various application areas. The findings indicated that the degradation level was always low, less than 2% in all the cases. The minimum degradation was found to be at Intelligent Transportation at 0.8% and Networking and SDN at the highest at 1.6. These findings established robust cross-domain generalization, which shows that the suggested fusion-based intelligent decision support system did not exhibit any significant changes in accuracy and reliability when cross-domain generalization was done.

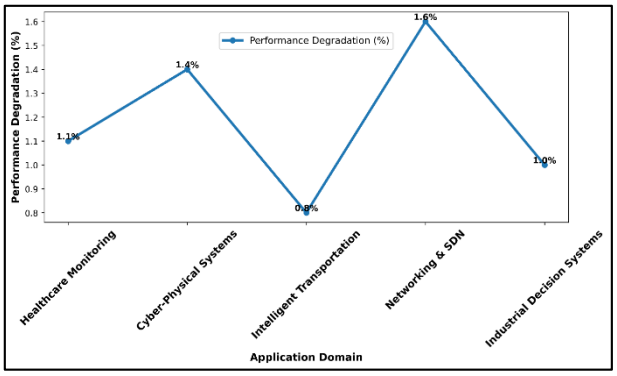


Figure 6. Cross-Domain Performance Degradation Analysis of the Proposed Decision Support System

7. DISCUSSION

The experimental findings showed conclusively that the proposed intelligent software system was very useful in enhancing the quality of decisions in various fields. The fusion-based method was better than rule-based, machine learning-only, and reinforcement learning-only in accuracy, precision, recall, and F1-score. These findings showed that learning, reasoning and adaptive policy optimization is an effective integration of the three to reduce false decisions and enhance overall robustness. The Latency analysis also indicated that the proposed system managed to gain significant responsiveness, which validated the appropriateness of this system to be used in real-time and time-sensitive decision making processes. Cross-domain testing found that there was very little loss in performance, which justified that the system was able to extrapolate learned decision intelligence to an outside context of applications.

Regarding a real-life implementation, the results have indicated the possibility of implementing a common decision support platform in mixed settings, including healthcare monitoring, cyber-physical systems, intelligent transportation, networking, and industrial work. The layered and modular architecture did not require a redesign of the underlying system as it enabled easy integration of varied data sources and domain specific constraints. The achieved efficiency and convergence time indicated that the system was capable of working with real-world workloads and having minimal computational overhead. These properties rendered the approach proposed to be appropriate in large-scale, distributed, and resource-constrained deployments where adaptability and scalability were the most crucial factors.

The main strengths of the proposed system were trust, explainability, and reliability of the decisions. The explainability mechanisms allowed the interpretation of decisions to be made transparently using the feature attribution, rule tracing, and policy relevance analysis.

These functionalities enhanced the confidence of the users, as well as human-in-the-loop supervision, especially in safety critical applications. The high reliability scores over all domains revealed that the system did not change the decision behavior in the context of different data conditions and levels of noise. The system integrated with regulatory and operational needs as it allowed the introduction of transparency and auditability to the decision-making pipeline, which could ensure the reliable adoption in the real-world.

Although these were the benefits, the proposed system had some limitations. The combination of several intelligence units made the systems more complex and demanded very specific parameter adjustments to achieve the best balance between the accuracy, latency, and safety goals. Policies of reinforcement learning required enough interaction information that may not be available in areas with limited feedback. Also, as much as the explainability mechanisms enhanced transparency, they added computational overhead to post-hoc analysis. These limitations might be overcome in future work by fixing the automated hyperparameter optimization, lightweight explanation methods, and domain-specific transfer learning strategies to make the work even more efficient and adaptable.

8. CONCLUSION AND FUTURE WORK

This paper has proposed a coherent intelligent software system and multi-domain decision support, which counterparts the shortcomings of the traditional domain-specific and isolated decision-making methods. The framework suggested combined hybrid learning, rule-based reasoning, policy optimization based on reinforcement learning, and decision fusion and weighting based on context. The experimental evidence showed that the proposed fusion-based system always outperformed base techniques in all the metrics assessed. The proposed system performed the best in terms of decision accuracy (97.6%), precision (97.2%), recall (98.1%) and F1-score (97.6) compared to the rule-based, machine learning-only and reinforcement learning-only ones, which supported the effectiveness of coordinated intelligence. Additional analysis whose latency analysis revealed a major decrease in average and worst-case response time with a maximum latency decrease of 48.2 percent confirmed real-time applicability. Cross-domain assessments indicated performance reduction of less than 2% which represents strong generalization and strong robustness in application domains which are heterogeneous. The findings highlighted the effects of smart multi domain decision support systems in facilitating trustful, flexible, and scalable decision making. The given architecture offered explainability, trust, and efficiency in one solution, which has solved the practical deployment challenges in both safety-critical and data-intensive settings. The flexibility of the system enabled it to be used in various ways like healthcare monitoring, cyber-physical systems, intelligent transportation, networking, and industrial operations because they are accurate, fast, and reliable. The future studies can build on this study by adding automated hyperparameter optimization and adaptive weight learning to augment decision fusion. The combination of federated and transfer learning approaches might increase the scalability and privacy protection in distributed fields.

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