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Strategic Selection of Application Area for Optimizing Computational Complexity in Explainable Decision Support System Using Multi-Criteria Decision Analysis (MCDA)

Ijeoma Noella EZEJI
Department of Computer Science, University of Zululand
Kwadlangezwa, Kwazulunatal, South Africa

Matthew Olusegun ADIGUN
Department of Computer Science, University of Zululand
Kwadlangezwa, Kwazulunatal, South Africa

Olukayode OKI
Department of Information Technology, Walter Sisulu University
East London, Eastern Cape, South Africa

ABSTRACT

Explainable Decision Support Systems (XDSS) have emerged as a critical tool for integrating artificial intelligence (AI) into decision-making processes, combining predictive accuracy with interpretability to foster user trust and accountability. Despite their increasing adoption across various domains, XDSS face significant computational challenges, including data complexity, scalability, real-time processing demands, and ensuring fairness and robustness. These challenges are further compounded by the unique requirements and constraints of different application areas, which directly influence system performance and utility, making the strategic selection of application areas a crucial step in optimizing XDSS performance. Therefore, this paper employs an adaptation of Multi-Criteria Decision Analysis (MCDA) to systematically evaluate and rank potential application areas based on domain-specific factors such as data characteristics, explanation requirements, and computational constraints. Through a detailed analysis of challenges and application contexts, this paper underscores the importance of domain selection in maximizing the practical utility and computational efficiency of XDSS. The findings emphasize that selecting the right application area is foundational to ensuring XDSS efficiency and highlight how the MCDA framework can be extended to support further configuration decisions within selected domains. This paper contributes to the strategic planning and development of future XDSS frameworks, offering guidance for developers and business leaders aiming to implement these systems more effectively.

Keywords: Computational Complexity; Explainable Decision Support Systems (XDSS); Multi-Criteria Decision Analysis (MCDA); Application Area; Selection.

1. INTRODUCTION

Explainable Decision Support Systems (XDSS) are at the forefront of integrating artificial intelligence (AI) with user-centric explanations that is enabled by explainable artificial intelligence (XAI), providing clarity and justification for automated decisions [1]. In domains ranging from healthcare and finance to urban planning and emergency management, XDSS helps stakeholders make informed decisions by providing transparent insights into the complex algorithms that underpin these systems. In healthcare to be specific, XDSS can enhance accountability and trust in AI systems [2], while in biomedicine, they can make AI decisions trustworthy for physicians and patients [3]. However, one of the persistent challenges in the deployment of XDSS is managing the inherent computational complexity that comes with processing large, diverse datasets and executing complex algorithms.

As the complexity of datasets and decision-making processes increases, so does the computational load on XDSS [4]. This can lead to slower response times and decreased efficiency, ultimately affecting the system's performance and user satisfaction. Optimizing computational complexity within XDSS is therefore essential, not only to enhance system performance but also to maintain and improve the quality of decision-making [5]. As XDSS are deployed in environments requiring real-time or near-real-time analytics, such as emergency rooms and financial trading floors, the systems must operate with high efficiency. This need for speed and accuracy places substantial computational demands on the systems, necessitating robust data management, processing capabilities, and scalable solutions.

Despite the increasing adoption of Explainable Decision Support Systems (XDSS) across various domains, there remains a significant gap in understanding how the choice of application area impacts the optimization of computational complexity. Addressing this gap requires a comprehensive representation of the application domain and careful consideration of how different requirements and factors fit together [6]. Current research primarily focuses on improving individual aspects of XDSS, such as explainability and algorithmic efficiency, but often overlooks the holistic influence of application context on these improvements. This gap is critical because the demands on computational resources and the necessity for transparent decision-making vary greatly across different sectors, leading to inconsistent performance and suboptimal utilization of XDSS capabilities.

Therefore, the focus of this paper is on the strategic selection of application areas as a means to maximize the benefits of computational optimization in XDSS using Multi-Criteria

Decision Analysis (MCDA) to systematically evaluate and select application areas that present the greatest opportunity for computational optimizations in XDSS. The choice of application area significantly influences the design and functionality of XDSS, dictating the types of data processed, the complexity of the decision-making required, and the specific needs for explainability.

Following that the paper will provide a comprehensive understanding of how strategic choices in application area selection can guide the optimization of computational efficiency and enhance the overall utility of Explainable Decision Support Systems, the contributions of the paper are as follows:

1) introduces a systematic framework using Multi-Criteria Decision Analysis (MCDA) for selecting application areas where computational optimizations can be most effective. This framework guides in identifying areas that benefit significantly from computational efficiency improvements.
2) Establishes a set of criteria for selecting application areas for XDSS based on computational complexity, relevance, and impact on decision-making.
3) Provides a detailed comparative analysis of application areas like healthcare, finance, and retail, identifying where computational optimizations in XDSS can be most effective.

The remainder of the paper is organized as follows: Section 2 explores the background and context of XDSS, discussing its core components, common computational challenges, and the influence of different application areas on its functionality. Section 3 establishes the criteria for selecting application areas and reviews potential sectors where XDSS could be particularly impactful. The review of the potential application area is presented in section 4 while in section 5 through case studies and comparative analyses, the article will demonstrate successful implementations and draw lessons on strategic application area selection. Finally, it will discuss the broader strategic implications for both developers and business leaders, address potential challenges and ethical considerations, and suggest future research directions to continue advancing the field.

2. BACKGROUND AND CONTEXT

XDSS have emerged as a transformative technology, enabling informed decision-making by combining the predictive power of advanced AI models with interpretability that enhances user trust and accountability. This section provides a foundational understanding of XDSS, outlines the computational challenges they face, and emphasizes the critical importance of strategically selecting the right application domain to optimize their performance and utility.

Overview of XDSS

XDSS represent a sophisticated integration of advanced computational models with interactive decision-support interfaces. These systems are designed to aid human decision-makers by providing actionable insights derived from complex data analyses while ensuring transparency in the decision-making process. The core components of an XDSS as depicted by the XAI concept diagram in Figure 1. [7] typically include and synthesized as follows:

Data Processing Module: This component handles the ingestion, cleaning, and transformation of large datasets to prepare them for analysis. It ensures that data from various sources is normalized and pre-processed to a consistent format suitable for the analytical engine.

Analytical Engine: This module implements machine learning algorithms or statistical models to analyze the processed data and generate predictions or recommendations. It forms the computational core of XDSS, transforming raw data into meaningful insights.

Explanation Framework: A crucial component that generates interpretable outputs explaining the reasoning behind the system's decisions to the end-users. This ensures transparency and helps build trust in the system by providing justifications for the decisions made.

User Interface: This component provides a platform for users to interact with the system, input data, and receive explanations in an understandable format. It bridges the gap between complex computational processes and the end-users, facilitating easy access and interpretation of the insights generated.

Computational Challenges in XDSS

The implementation of XDSS encounters a range of computational challenges that impact performance, scalability, and usability. These challenges are influenced not only by the inherent complexity of integrating explainable artificial intelligence (XAI) into decision-making workflows while maintaining efficiency and interpretability but also by the

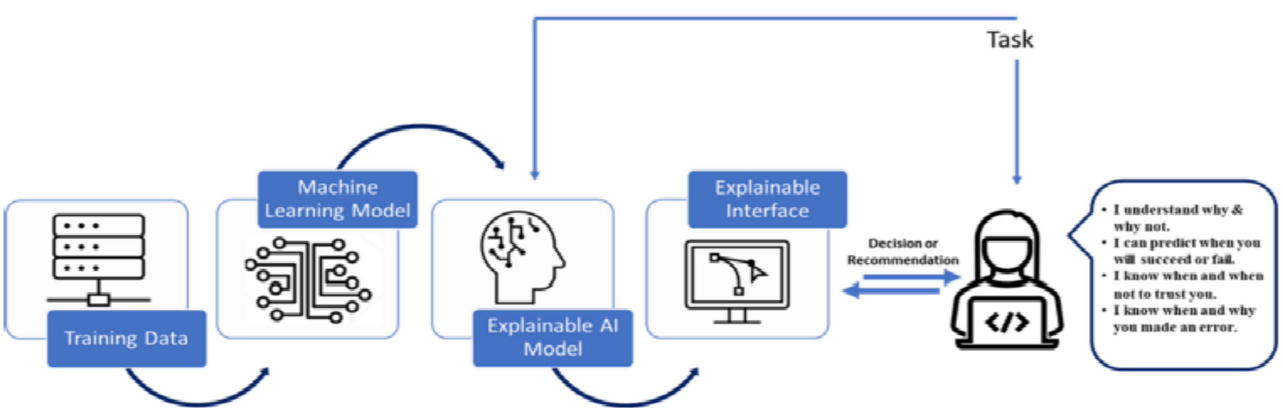

Figure 1: Overview of XAI Concept

specific requirements of the application domain. Strategic selection of application domains plays a critical role in managing these challenges effectively, as different domains offer unique opportunities for optimizing computational complexity. The following thematically outlines the key challenges in XDSS and highlights how domain-specific considerations shape them.

Algorithmic Efficiency and Complexity: The complexity of algorithms used in XDSS significantly affects their computational performance. Generating explanations often requires resource-intensive processes, such as sampling, perturbation, or surrogate modeling (e.g., LIME, SHAP). High-dimensional datasets and intricate models further increase computational demands, highlighting the need for efficient algorithms that strike a balance between accuracy and interpretability. Poorly optimized algorithms can lead to excessive latency, especially in real-time applications.

Data Volume and High Dimensionality. The vast amounts of data that XDSS needs to process can lead to significant computational demands, requiring robust data management and processing capabilities. traditional XAI techniques often struggle with high-dimensional data due to computational constraints and cognitive burden of interpreting complex explanations [8], [9]. Ribeiro (2021) highlights the impact of dataset complexity on model explainability, suggesting that more complex datasets may require more sophisticated XAI techniques [10]. This is in line with the broader understanding of computational complexity, which considers the inherent difficulty of problems and the efficiency of algorithms in solving them

Real-Time Constraints. Real-time constraints in Explainable AI (XAI) pose significant challenges for AI systems, particularly in safety-critical applications [11]. The need for real-time or near-real-time analytics in environments like emergency rooms or financial trading floors pressures XDSS to provide explanations within stringent timeframes, to operate with high efficiency and minimal latency. Generating accurate and interpretable explanations under time constraints requires efficient algorithms and optimized workflows to balance speed and reliability. Additionally, interpretability techniques like SHAP and LIME, while providing valuable insights, are computationally intensive and may not be practical for real-time applications or large datasets [6]. This requirement underscores the importance of optimizing computational complexity to ensure that XDSS can deliver timely and actionable insights without delays.

Complexity of Models. The complexity of predictive or prescriptive models used in XDSS can make them computationally expensive, particularly when they involve deep learning or other advanced AI techniques. The application of XAI in addressing these complex problems is an ongoing challenge, with the need for more efficient algorithms and techniques [12]. A key challenge is balancing model complexity and interpretability, as simplifying highly accurate models like DNNs for better explainability can reduce accuracy, which is unacceptable in critical applications. Efforts must focus on methods that preserve performance while ensuring sufficient explanations [13].

Scalability. As XDSS applications grow in any aspect, the systems must scale without a loss in performance. Scaling XDSS to accommodate larger datasets, more users, more complex decision scenarios or additional functionalities introduces challenges related to computational resource management. Ensuring explanation accuracy and responsiveness under increased workload necessitates advanced optimization techniques, which in turn introduce their own complexities. Formal explainability approaches, which offer rigorous guarantees but face scalability challenges, particularly for neural networks [14]. Ensuring that XDSS can handle increased loads while maintaining efficiency and accuracy is crucial for their success. There may be a need to weigh the cost of explainability methods, consider alternative or approximate solutions, and potentially invest in more powerful computational resources or optimize the methods for better scalability [6].

Interpretability and Explainability Needs. Different applications have varying requirements for interpretability and explainability, complicating the development of generalized solutions [15]. Interpretability is often judged according to the specific requirements of the application area. For example, the interpretability needs in healthcare for diagnosing patients are different from those in industrial anomaly detection. This variability necessitates the development of standardized interpretability metrics that can quantitatively assess this characteristic across different contexts. A key idea in interpretability research is that the main reason for an ML- or CI-based system to require interpretability is some form of incompleteness in the problem formulation. This may include limited understanding of the problem or a mismatch between modeling objectives and application goals. Recognizing these diverse needs highlights the importance of selecting application areas that can benefit most from computational optimizations while ensuring that the models remain interpretable and explainable.

Trade-Off Between Fidelity and Simplicity: Explanations must balance fidelity (accurately reflecting model behavior) and simplicity (being understandable to users). High-fidelity explanations often demand greater computational resources, while overly simplified explanations risk omitting key insights. The interplay between complexity, fidelity, and coverage in surrogate explanations is crucial for effective XAI [16]. Achieving this balance is a central challenge in XDSS development.

Robustness and Fairness: Recent research has highlighted the interconnected nature of fairness, robustness, and explainability in AI systems [17], [18], [19]. Ensuring explanations remain robust in adversarial scenarios or under noisy data conditions is a complex challenge, particularly in domains like cybersecurity or finance, where adversarial behavior is common. Additionally, fairness requirements in domains such as healthcare and employment demand computationally intensive checks. Choosing domains with lower adversarial risks or simplified fairness requirements can reduce these burdens.

User-Centric Customization: Studies emphasize the need to consider different stakeholder groups and their unique interpretability requirements [15], [20]. Different application domains involve diverse user groups, each with unique interpretability needs. For example, healthcare professionals may require detailed, domain-specific explanations, whereas retail consumers may benefit from simpler, generalized insights. Tailoring explanations to user needs increases computational complexity, but strategically selecting domains with homogeneous user bases can streamline customization efforts.

Explanation Delivery Formats: The computational complexity of delivering explanations in interpretable formats, such as natural language, decision rules, or visualizations, depends on domain requirements. Researchers have classified XAI methods based on their output formats, such as feature attribute, instance, and decision rules/trees [21], [22]. For instance, domains like education or legal analysis may demand detailed textual or graphical explanations, while others, like autonomous systems, may rely on simpler formats. Selecting domains with less demanding explanation delivery requirements can optimize computational efficiency.

These challenges highlight the necessity for continuous advancements in computational optimization techniques to improve the performance and scalability of XDSS. The strategic selection of application areas is crucial for optimizing computational complexity in XDSS.

Importance of Choosing the Right Application Area for Optimizing Computational Complexity

The computational complexity of XDSS is closely tied to the characteristics of the application domain in which they are deployed. Different domains pose varying levels of challenges based on the nature of data, explanation requirements, and time sensitivity. Selecting the right application domain strategically can help optimize computational complexity while maximizing the system's utility and impact.

In a real-world application context, interpretability might be judged according only to the specific requirements of the application area. For example, the requirements for diagnosis in oncology and for anomaly detection in industrial production have little in common [23]. This acknowledgment that different application areas have unique interpretability and explainability needs is crucial. Different sectors face varied challenges and priorities when it comes to decision support systems. For instance, healthcare applications prioritize the accuracy and explainability of diagnostic models, while industrial applications may focus more on the detection of anomalies in production processes and the efficiency of these detections.

Selecting the right application area is not just about addressing computational complexity; it also involves aligning with the specific demands and priorities of that sector. This strategic selection ensures that the XDSS can deliver meaningful, context-appropriate insights that are both computationally efficient and interpretable by the end-users. By focusing on an application area with clearly defined priorities and challenges, the design and implementation of XDSS can be strategically optimized. This approach not only reduces computational complexity but also enhances the system's ability to provide meaningful and user-relevant insights in real-world scenarios.

3. METHODOLOGY

This study employs the Multi-Criteria Decision Analysis (MCDA) framework adapted to strategically select application areas for optimizing computational complexity in XDSS. MCDA is predominantly used in healthcare decision making. It provides a robust framework for decision-making by allowing the assessment of multiple criteria that affect a particular choice [24]. Therefore, it is adapted to ensure that the selected application areas are best suited to leverage the benefits of computational optimizations while addressing the specific needs and challenges inherent to each sector.

This adaptation of the MCDA framework provides a systematic and quantifiable method for selecting the most appropriate application area for deploying XDSS, ensuring that the decision is grounded in thorough analysis and strategic alignment and is provided as follows in Figure 2.

The methodology for selecting application areas in Explainable Decision Support Systems (XDSS) using Multi-Criteria Decision Analysis (MCDA) follows a structured, step-by-step approach to ensure a robust and transparent evaluation:

Figure 2: Adapted MCDA Framework for Selecting Application Areas in XDSS

Step 1 - Defining the Decision Problem: The first step clearly identifies the decision problem, focusing on selecting application areas where computational complexity optimization is critical. This step ensures that the scope of the analysis aligns with the goals of enhancing XDSS efficiency while maintaining explainability.

Step 2 - Identifying and Structuring Criteria: Relevant criteria are identified through comprehensive literature reviews and domain analysis, ensuring that they are specific, measurable, and aligned with the objectives.

Step 3 - Measuring Performance of Alternatives: A three-point Likert scale was developed to assess the quality of each criterion, representing high, medium, and low performance levels.

Step 4 - Scoring Alternatives: Alternatives in the context of the study, application areas are scored based on their performance against the identified criteria. Standardized scoring methods are employed to ensure consistency, and validation is conducted to minimize errors and ensure reliability.

Step 5 - Weighting Criteria: Criteria are weighted to reflect their relative importance using techniques like the Analytic Hierarchy Process (AHP). This ensures alignment with stakeholder priorities and strategic objectives, making the evaluation process transparent and objective.

Step 6 - Aggregating Scores: Aggregated scores are calculated by combining the performance scores and weights using appropriate aggregation functions (e.g., weighted sums). The results are validated to ensure robustness and consistency in the ranking of application areas.

Step 7 - Sensitivity Analysis: Potential uncertainties in the decision-making process are addressed through sensitivity analysis methods, such as Monte Carlo simulations or weight adjustments. This step evaluates how variations in criteria weights or performance scores impact the final rankings, ensuring the robustness of the results.

Step 8 - Reporting Findings and Recommendations: Finally, the results are synthesized and reported, providing key insights and actionable recommendations for XDSS deployment. This includes highlighting the strengths and limitations of the MCDA approach, as well as discussing the practical implications for optimizing computational complexity in the selected application areas.

4. POTENTIAL APPLICATION AREAS

Explainable Decision Support Systems (XDSS) have the potential to significantly enhance decision-making processes across various domains. To provide a meaningful context for this section, this study builds upon existing research that previously presented various application areas through case studies on Healthcare, finance and business domains respectively [5]. To provide a broader perspective, additional application areas identified in other studies have been synthesized and included [13], [25]. The section aligned with Step 1 of the MCDA process which is to define the decision problem and specifically identify potential application areas where computational complexity optimization is both critical and feasible. This ensures that the findings remain applicable to similar contexts across other domains, laying a solid foundation for the systematic evaluation that follows.

Healthcare

In healthcare, XDSS can manage vast amounts of patient data, including medical histories, diagnostic images, and treatment plans, ensuring accurate and timely access to patient information. XAI techniques are being applied to various healthcare domains, including patient monitoring systems [26], pharmacovigilance [27], and clinical prediction models [28]. This is crucial for improving the quality of care and enabling personalized treatment. Additionally, XDSS can assist in diagnosing diseases and planning treatment by analyzing patient data and medical research [29], thus enhancing diagnostic accuracy and suggesting evidence-based treatment options, reducing the risk of human error. In emergency rooms and triage assessments, XDSS can provide real-time data analysis and decision support, which is critical for effective and timely emergency response, ensuring that patients receive the appropriate level of care promptly [30] [31].

Finance

XDSS span various financial applications, including credit management, stock predictions, and anomaly detection [32]. Explainability plays a vital role in the finance sector, significantly enhancing risk assessment, fraud detection, and customer service [33]. XDSS can enhance risk assessment by analyzing financial data to manage risks in investments, loans, and other financial activities [34], [35]. This improves decision-making accuracy and reduces financial losses. XDSS is also pivotal in fraud detection, where it identifies fraudulent activities by analyzing transaction data and identifying anomalies, thus protecting financial institutions and customers. Additionally, XDSS helps manage and analyze customer data to improve service and develop personalized financial products, enhancing customer satisfaction and loyalty.

Business

Explainable Decision Support Systems (XDSS) can significantly enhance various business operations including strategic planning, supply chain management, and customer relationship management. In strategic planning, XDSS analyzes market trends, competitive landscapes, and internal performance metrics, aiding businesses in making informed strategic decisions aligned with their long-term goals. However, integrating diverse data sources and providing actionable insights for business leaders can be challenging. In supply chain optimization, XDSS analyzes data on suppliers, inventory levels, and logistics, enhancing operational efficiency, reducing costs, and improving supply chain resilience [36]. Managing complex supply chain data and delivering actionable insights are primary challenges. For Customer Relationship Management (CRM), XDSS analyzes customer interactions and feedback, improving customer satisfaction and loyalty through personalized experiences. Ensuring data privacy and providing easily understandable insights for CRM professionals are significant challenges.

Transport

In the transport sector, XDSS can enhance route optimization, traffic management, and logistics operations. Studies have investigated XAI methods for understanding user experience in sustainable transport [37], improving conflict resolution in air traffic management [38], and enhancing mobile traffic classification [39]. XAI has been applied to analyze risk factors in road accidents [40] and interpret traffic flow forecasting models [41]. In the context of intelligent connected vehicles, XAI has been explored for intrusion detection and mitigation [42], as well as for traffic detection in autonomous systems [43]. Additionally, XAI techniques have been employed to explain flight take-off time delay predictions to air traffic controllers [44]. These systems can analyze real-time traffic data to minimize delays, optimize delivery routes, and allocate resources efficiently.

Manufacturing and Industry

In manufacturing and industrial settings, XDSS can optimize production processes, improve operational efficiency from product design to quality control and predictive maintenance [45]. These systems can analyze sensor data from machinery, monitor production lines, and predict equipment failures, enabling proactive maintenance and reducing downtime [46]. By leveraging real-time data, XDSS can identify inefficiencies, optimize resource allocation, and streamline supply chain management. Additionally, they can assist in product design and testing by analyzing performance metrics and simulating scenarios to improve outcomes [47]. In quality assurance, XDSS can detect anomalies in production, ensuring that products meet required standards [48]. For example, in industries like automotive or electronics, XDSS can identify defects early in the production cycle, minimizing waste and improving overall product reliability.

Education

In education, XDSS can support personalized learning by analyzing student performance data and adapting teaching methods accordingly [49]. These systems can help educators identify learning gaps, recommend tailored interventions, and optimize curricula based on analytics. Additionally, XDSS can assist administrators in resource allocation and policy planning.

5. CRITERIA FOR APPLICATION AREA SELECTION

The selection of criteria begins with a thorough understanding of the functional requirements and computational challenges inherent in XDSS and it is aligning with Step 2 of MCDA which is selecting and structuring criteria. Usually, these criteria are derived from a combination of technical needs, stakeholder expectations, and the strategic objectives of the systems. For choosing an appropriate application domain for XDSS involves evaluating several key factors to ensure optimal performance, usability, and compliance with broader requirements. The following considerations are essential in guiding domain-neutral decision-making for deploying XDSS:

Data Characteristics

The data within the application domain plays a critical role in shaping the design and implementation of XDSS. Data explainability, an essential concept, ensures that the datasets used to train AI models are comprehensible, reliable, and of high quality [50]. This is particularly relevant as the behavior and performance of XDSS are heavily influenced by the characteristics of the input data. Data characteristics such as volume, velocity, variety, veracity, and validity play a critical role in shaping the design and reliability of AI-based decision-making algorithms [51]. These factors are essential considerations for data-driven decision-making, as they directly impact the quality, performance, and trustworthiness of AI systems in handling complex data [52]. High-volume datasets demand robust processing and storage capabilities, while data structure, whether structured, semi-structured, or unstructured affects the complexity of integration and analysis. Complex datasets with high dimensionality or heterogeneity require advanced computational techniques to ensure efficient processing and meaningful explanations. High-dimensional or heterogeneous datasets add to computational challenges, emphasizing the importance of selecting domains where XDSS can effectively handle data complexities without compromising performance.

Explanation Requirements (Fidelity vs. Simplicity)

The need for interpretability varies significantly across applications [53], creating a trade-off between fidelity and simplicity [16]. High-fidelity explanations provide detailed insights into model behavior but often come with increased computational demands. Conversely, simpler explanations prioritize accessibility and ease of understanding, potentially sacrificing some level of detail. When selecting a domain, it is essential to balance these requirements in a way that matches user expectations and system objectives while maintaining computational efficiency.

Real-Time Processing Needs

Timeliness is a critical consideration in many decision-support contexts [54]. Domains with real-time or near-real-time requirements necessitate XDSS implementations capable of delivering low-latency responses. Achieving this requires optimized workflows, lightweight algorithms, and scalable infrastructure. In contrast, domains with less stringent time constraints may allow for more computationally intensive approaches that prioritize depth and accuracy over speed. Ensuring that XDSS can meet the real-time demands of a domain is critical for its functionality and impact.

Scalability Demands

Scalability addresses the ability of XDSS to adapt to increasing data volumes, user bases, or operational demands over time [9]. Whether processing high transaction volumes, accommodating diverse user groups, or analyzing complex datasets, scalability ensures that the system can expand without degrading performance. When evaluating potential domains, it is important to consider how scalability requirements impact computational infrastructure and whether the XDSS can support anticipated growth efficiently

Ethical and Regulatory Constraints

Ethical and regulatory considerations are pivotal in ensuring that XDSS deployments adhere to societal norms and legal frameworks such as the EU's GDPR, HIPAA and NYC's ADS Law, aim to protect individual rights in data-driven technologies [55]. Issues such as fairness, transparency, and data privacy must be addressed to build trust and prevent unintended consequences. Regulatory requirements, such as those mandating interpretable decision-making or safeguarding sensitive information, vary across applications and can introduce additional computational challenges. A domain-neutral approach focuses on selecting domains where these constraints can be effectively managed within the system's design and operational framework.

6. PERFORMANCE MEASUREMENT

To measure the performance of each alternative in the MCDA process for XDSS, a three-point Likert scale was established to evaluate levels of performance across all identified criteria, aligning with Step 3 of the MCDA process. This step ensures a standardized and consistent assessment framework, enabling objective comparisons of alternatives. The measures of performance for each criterion are outlined in the final column of Table 1, representing high, medium, and low performance levels. For example, "Data Characteristics" was evaluated as 1 (high complexity), 2 (moderate complexity), or 3 (low complexity).

7. EVALUATION AND DECISION-MAKING PROCESS

This section of the paper delineates the meticulous process employed in the evaluation and decision-making phase of selecting application areas for optimizing computational complexity in XDSS using MCDA. The process is centred on four crucial activities such as scoring of alternatives, weighting of criteria, aggregation of scores and sensitivity analysis to derive a conclusive evaluation for each considered application area.

Scoring of Alternatives

The scoring of alternatives aligns with Step 4 of MCDA process, where the performance of each application area is systematically

Table 1: The criteria considered, definition and measurement levels

Criteria	Description	Reason for Inclusion	Measure of Performance
Data Characteristics	Evaluates data volume, structure, and complexity	Ensures XDSS can handle diverse data efficiently while maintaining performance	1 = High complexity (large, unstructured, or high-dimensional), 2 = Moderate complexity, 3 = Low complexity
Explanation Requirements	Assesses the trade-off between fidelity and simplicity in explanations	Aligns explanation complexity with user and system needs	1 = High fidelity (detailed), 2 = Moderate fidelity (balanced), 3 = Simple explanations (minimal detail)
Real-Time Processing Needs	Measures the urgency and timeliness of decision-making	Addresses latency constraints critical for time-sensitive decisions	1 = Real-time (milliseconds), 2 = Near real-time (seconds to minutes), 3 = non-time-sensitive (hours or more)
Scalability Demands	Evaluates potential for growth in data volume or user demand	Ensures the system can adapt to increasing scale without performance degradation	1 = Highly scalable (handles significant growth), 2 = Moderately scalable, 3 = Limited scalability
Ethical and Regulatory Constraints	Assesses fairness, transparency, and compliance requirements	Ensures the system meets legal and ethical standards	1 = High (stringent requirements), 2 = Moderate, 3 = Low (minimal requirements)

evaluated against the identified criteria were compiled into a performance matrix, as depicted in Table 2. A standardized scoring method was applied using a three-point Likert scale, which measures performance levels as high, medium, or low. This approach ensures a consistent, objective, and transparent evaluation framework.

Table 2: Performance Matrix for Potential Areas for Research in XDSS

Domain	Application Area	DC	ER	RPN	SD	ERC
Healthcare	Patient Monitoring Management	1	1	1	2	1
	Diagnosis and Treatment Planning	1	1	2	2	1
	Emergency Triage Assessment	2	2	1	2	1
Engineering	Predictive Maintenance	2	2	1	2	2
	Design Optimization	2	1	2	1	1
	Quality control/Safety Analysis	1	1	1	1	1
Transportation	Traffic Management	2	2	1	2	2
	Autonomous Vehicles	1	1	1	1	2
	Fleet Management	2	2	1	2	2
Finance	Risk Assessment	1	1	2	1	1
	Fraud Detection	1	1	1	1	1
	Stock Prediction	2	1	3	2	2
Business	Strategic Planning	3	2	2	3	2
	Supply Chain Optimization	2	1	2	1	2
	Customer Relationship Management	2	2	3	1	2
Education	Adaptive Learning Models	3	2	3	2	2
	Student Performance Analytics	2	1	2	1	2
	Curriculum Design Optimization	1	1	2	2	1

DC = Data Characteristics, ER = Explanation Requirements, RPN = Real-Time Processing Needs, SD = Scalability Demands, ERC = Ethical and Regulatory Constraints

Weighting of Criteria

The weighting of criteria corresponds to Step 5 of the Multi-Criteria Decision Analysis (MCDA) process, where the relative importance of each criterion is determined to reflect strategic priorities and stakeholder objectives. Weighting ensures that criteria contributing more significantly to decision-making receive higher influence in the final evaluation.

In this study, the Analytic Hierarchy Process (AHP) was employed to assign weights to the criteria. This technique provides a systematic and objective method for determining the importance of each criterion by comparing them pairwise. The assigned weights reflect the degree to which each criterion impacts the suitability of an application area for XDSS deployment. The pairwise comparisons required for AHP were conducted by the authors, based on insights synthesized from existing literature [25], [56] on XDSS applications and challenges.

The finalized weights were compiled and are presented in Table 3, providing a clear representation of the relative importance of each criterion. Higher weights were assigned to criteria such as Real-Time Processing Needs, Scalability Demands, and Data Characteristics, which are critical for optimizing computational complexity in XDSS.

Table 3: Proposed Weights for Criteria

Criteria	Weight	Rationale for Weight Assignment
Data Characteristics	0.20	Data volume, structure, and complexity significantly influence the computational burden and system design requirements.
Explanation Requirements	0.25	The trade-off between fidelity and simplicity impacts the usability and interpretability of XDSS, particularly in high-stakes applications.
Real-Time Processing Needs	0.25	Real-time or near-real-time requirements are critical for time-sensitive applications like healthcare triage or autonomous systems.
Scalability Demands	0.20	Scalability ensures the system can handle increasing data and user loads, making it crucial for long-term viability.
Ethical and Regulatory Constraints	0.10	Legal and ethical compliance are essential in regulated sectors like healthcare and finance, affecting trust and adoption.

Aggregation of Scores

The aggregation of scores aligns with Step 6 of the Multi-Criteria Decision Analysis (MCDA) process, where the performance scores of each alternative are combined with their corresponding criteria weights to generate a final ranking. This step ensures that both the performance of alternatives and the relative importance of criteria are accounted for in a systematic and transparent manner.

To aggregate the scores, a weighted sum method was applied. The performance scores for each criterion, obtained in Step 4, were multiplied by the respective weights determined in Step 5. The weighted scores were then summed for each application area to produce a Total Weighted Score, reflecting the overall suitability of the alternative.

Aggregated Score=∑(Score for each criterion×Weight of the criterion)

The results of this aggregation process are presented in Table 4, which displays the total weighted scores for all evaluated application areas as well as the ranking. These scores provide a clear basis for ranking the alternatives, with higher scores indicating greater alignment with the evaluation criteria and strategic objectives.

Sensitivity Analysis

The sensitivity analysis aligns with Step 7 of the Multi-Criteria Decision Analysis (MCDA) process, where the robustness of the aggregated scores and rankings from Step 6 is tested under varying conditions. This step ensures that the evaluation results remain consistent and reliable, even when weights assigned to

Table 4: Aggregated Weighted Scores

Domain	Application Area	DC	ER	RPN	SD	ERC	AWS	Rank
Healthcare	Patient Monitoring Management	0.2	0.25	0.25	0.4	0.1	1.2	4
	Diagnosis and Treatment Planning	0.2	0.25	0.5	0.4	0.1	1.45	7
	Emergency Triage Assessment	0.4	0.5	0.25	0.4	0.1	1.65	11
Engineering	Predictive Maintenance	0.4	0.5	0.25	0.4	0.2	1.75	12
	Design Optimization	0.4	0.25	0.5	0.2	0.1	1.45	6
	Quality control/Safety Analysis	0.2	0.25	0.25	0.2	0.1	1	1
Transportation	Traffic Management	0.4	0.5	0.25	0.4	0.2	1.75	12
	Autonomous Vehicles	0.2	0.25	0.25	0.2	0.2	1.1	3
	Fleet Management	0.4	0.5	0.25	0.4	0.2	1.75	12
Finance	Risk Assessment	0.2	0.25	0.5	0.2	0.1	1.25	5
	Fraud Detection	0.2	0.25	0.25	0.2	0.1	1	1
	Stock Prediction	0.4	0.25	0.75	0.4	0.2	2	15
Business	Strategic Planning	0.6	0.5	0.5	0.6	0.2	2.4	17
	Supply Chain Optimization	0.4	0.25	0.5	0.2	0.2	1.55	9
	Customer Relationship Management	0.4	0.5	0.75	0.2	0.2	2.05	16
Education	Adaptive Learning Models	0.6	0.5	0.75	0.4	0.2	2.45	18
	Student Performance Analytics	0.4	0.25	0.5	0.2	0.2	1.55	9
	Curriculum Design Optimization	0.2	0.25	0.5	0.4	0.1	1.45	7

DC = Data Characteristics, ER = Explanation Requirements, RPN = Real-Time Processing Needs, SD = Scalability Demands, ERC = Ethical and Regulatory Constraints, AWS =Aggregated Weighted Score

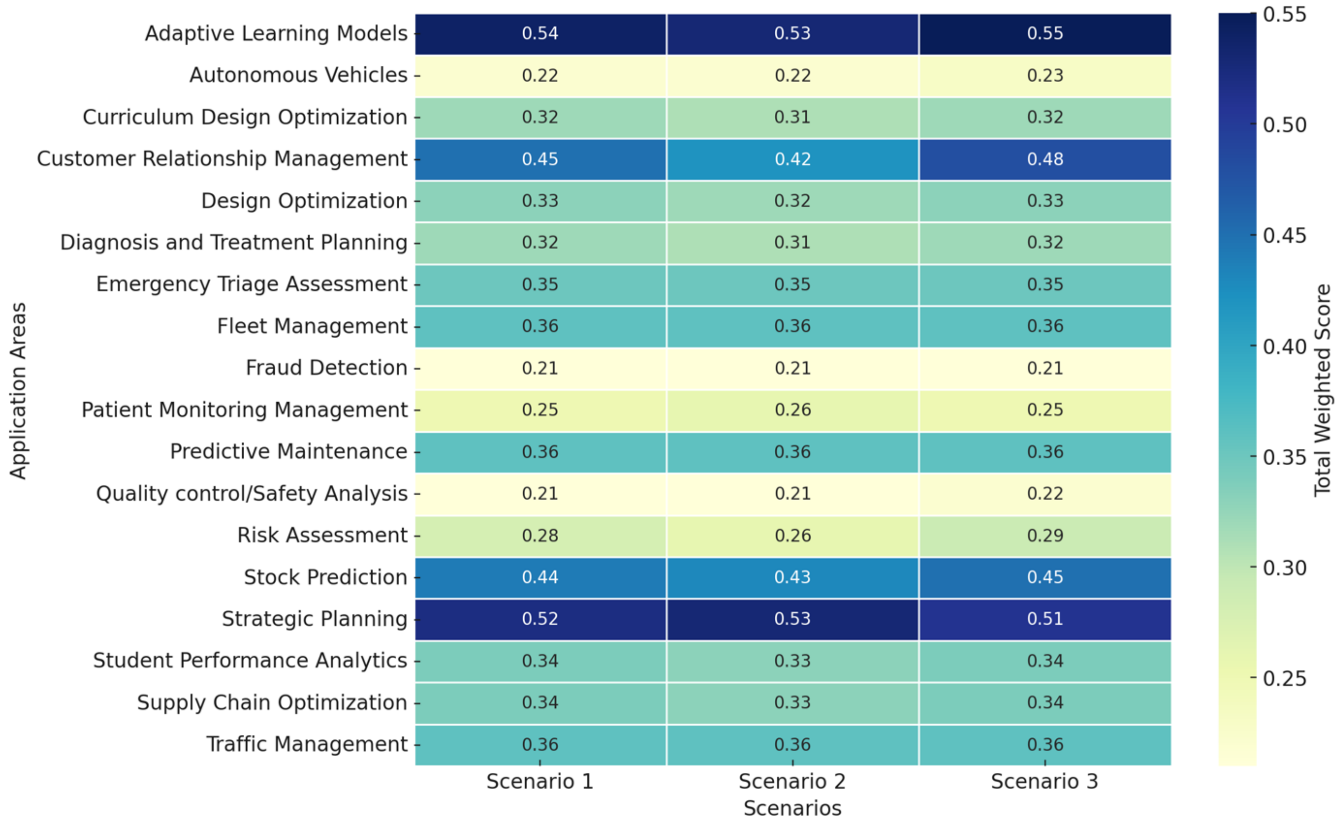

Figure 3: Sensitivity Analysis on Impact Weight Adjustments

key criteria are adjusted to reflect changes in strategic priorities or assumptions.

To conduct the analysis, weights for critical criteria such as Real-Time Processing Needs (RPN) and Data Characteristics (DC) were systematically varied across three scenarios as depicted in figure 3:

- Scenario 1 prioritized data complexity and real-time processing needs.
- Scenario 2 emphasized scalability while reducing the importance of explanation requirements.
- Scenario 3 focused on explanation fidelity and real-time decision-making, aligning with time-sensitive and high-stakes applications.

The results revealed that high-ranked application areas, such as Patient Monitoring Management and Fraud Detection, maintained stable positions across all scenarios, demonstrating the robustness of the MCDA framework. In contrast, areas with moderate initial scores, like Traffic Management and Stock Prediction, exhibited greater sensitivity to changes in specific criteria weights. This highlights the importance of accurately prioritizing criteria to reflect organizational goals and the impact of computational complexity.

The sensitivity analysis validated the reliability of the evaluation framework. While minor shifts occurred, the overall rankings remained stable for top-ranked application areas, providing stakeholders with confidence in the consistency and resilience of the decision-making process. This step underscores the credibility of the selected application areas for XDSS deployment, ensuring they remain relevant under varying assumptions and priorities.

8. DISCUSSION OF FINDINGS

This section discusses the selection and strategic implications of the top-ranked application areas, highlighting their alignment with key evaluation criteria and their potential impact. It also explores the challenges and considerations that may arise during implementation, including computational, ethical, and scalability concerns. Finally, actionable insights and recommendations are presented to guide stakeholders in deploying XDSS effectively in diverse domains, ensuring alignment with organizational goals and optimizing system performance.

Selection and Strategic Implications

The results identified Fraud Detection and Quality Control/Safety Analysis as the top-ranked application areas, both achieving the highest aggregated weighted score of 1.00. This strong performance highlights their alignment with key criteria, such as real-time decision-making needs, explanation requirements, and scalability:

Fraud Detection (Finance): Real-time anomaly detection, transparency in decisions, and regulatory compliance are critical in financial systems, making XDSS a suitable solution for enhancing security and stakeholder trust.

Quality Control/Safety Analysis (Engineering): XDSS can provide interpretable insights to ensure safety and optimize quality processes, particularly in high-risk industrial environments where explainability and real-time decision support are essential.

Other high-ranking areas included Autonomous Vehicles (Rank 3, score 1.10) and Patient Monitoring Management (Rank 4, score 1.20).

Autonomous Vehicles (Transportation): The need for low-latency, high-accuracy decisions in dynamic and safety-critical environments makes this area well-suited for XDSS.

Patient Monitoring Management (Healthcare): XDSS can process complex medical data in real time to improve patient outcomes and deliver transparent, actionable insights for healthcare providers.

Several mid-ranked application areas demonstrated strong potential but were influenced by specific criteria:

Emergency Triage Assessment (Healthcare): Ranked 5th with a score of 1.25, this application area requires real-time processing and accurate decision-making to prioritize patient care during emergencies. However, scalability and ethical constraints may add complexity to its implementation. XDSS can assist medical staff in quickly evaluating patient conditions and determining care priorities, improving efficiency and reducing human error.

Risk Assessment (Finance): Also ranked 5th with a score of 1.25, this area emphasizes scalability and explanation fidelity for managing financial risks. XDSS can streamline risk evaluation processes for loans and investments while ensuring transparency for compliance and stakeholder trust.

Lower-ranked areas, such as Stock Prediction (Rank 15, score 1.55) and Customer Relationship Management (CRM) (Rank 16, score 1.60), scored lower due to reduced real-time demands and lower complexity in explanation requirements:

Stock Prediction (Finance): While predictive accuracy is critical, the reduced focus on real-time needs and interpretability may limit the immediate priority for XDSS deployment.

Customer Relationship Management (Business): CRM applications focus more on personalization and scalability rather than explanation fidelity, which lowers the critical importance of XDSS.

However, these areas still hold value for future XDSS research, particularly in improving interpretability for end users and addressing scalability concerns for large datasets.

Challenges and Ethical Considerations

The results underscore several challenges and considerations for XDSS deployment:

Computational Complexity: High-ranked areas such as Fraud Detection and Emergency Triage Assessment require significant computational resources to manage real-time processing and large datasets. Optimizing workflows and resource allocation is crucial to address these challenges.

Explanation Trade-offs: Achieving a balance between explanation fidelity and simplicity remains critical, especially in time-sensitive applications like Emergency Triage and Autonomous Vehicles.

Scalability Constraints: Mid- and low-ranked areas may face challenges in scaling XDSS solutions to accommodate growing datasets or user bases while maintaining performance.

Ethical and Regulatory Compliance: Areas like healthcare and finance require strict adherence to transparency, fairness, and ethical standards to maintain trust and comply with regulations.

9. CONCLUSION

This study highlights the importance of a systematic, criteria-driven approach to evaluating potential application areas for XDSS. By employing MCDA framework, this research ensures that decision-making for XDSS deployment is guided by quantifiable, objective measures, integrating key factors such as data complexity, real-time processing needs, scalability, and ethical considerations. The findings highlight the necessity of aligning computational requirements with domain-specific constraints to enhance both system efficiency and explainability.

The findings identify high-ranking areas such as Fraud Detection, Quality Control/Safety Analysis, and Emergency Triage Assessment as ideal candidates for XDSS deployment. These areas demonstrate strong alignment with the evaluation criteria, showcasing their potential to benefit from explainable, computationally efficient decision support systems. At the same time, mid-ranked and lower-ranked areas, including Traffic Management and Stock Prediction, offer opportunities for future research and optimization, particularly in addressing specific challenges such as scalability and explanation fidelity.

The study also underscores several challenges must be addressed to ensure the practical implementation and long-term viability of XDSS. Managing computational complexity, balancing explanation fidelity with simplicity, and adhering to strict ethical and regulatory standards remain persistent concerns. Additionally, domain-specific constraints may impose limitations on XDSS performance, necessitating continuous refinement of evaluation criteria and methodologies. Strengthening transparency, fairness, and regulatory compliance is essential, particularly in sensitive sectors where trust and accountability are paramount.

Based on the findings, several actionable recommendations are proposed to guide XDSS deployment. Priority should be given to high-impact areas such as Fraud Detection and Patient Monitoring Management, where the need for real-time decision-making and interpretability is most critical. Efforts should focus on enhancing algorithmic efficiency and infrastructure to address the computational demands inherent in high-stakes, real-time environments. Additionally, developing scalable solutions is essential to ensure that XDSS can adapt to increasing data volumes and user demands, particularly in domains with growing datasets or expanding user bases. Finally, aligning XDSS deployments with transparency, fairness, and regulatory compliance is crucial to building stakeholder trust and meeting legal standards, especially in sensitive and regulated sectors.

Future research should explore additional application areas, refine evaluation criteria, enhance sensitivity analysis techniques, and strengthen validation with empirical studies. By addressing these avenues, XDSS can be optimized to deliver greater impact and utility across a broader range of domains, ensuring their adoption as reliable tools for decision support in increasingly complex environments.

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