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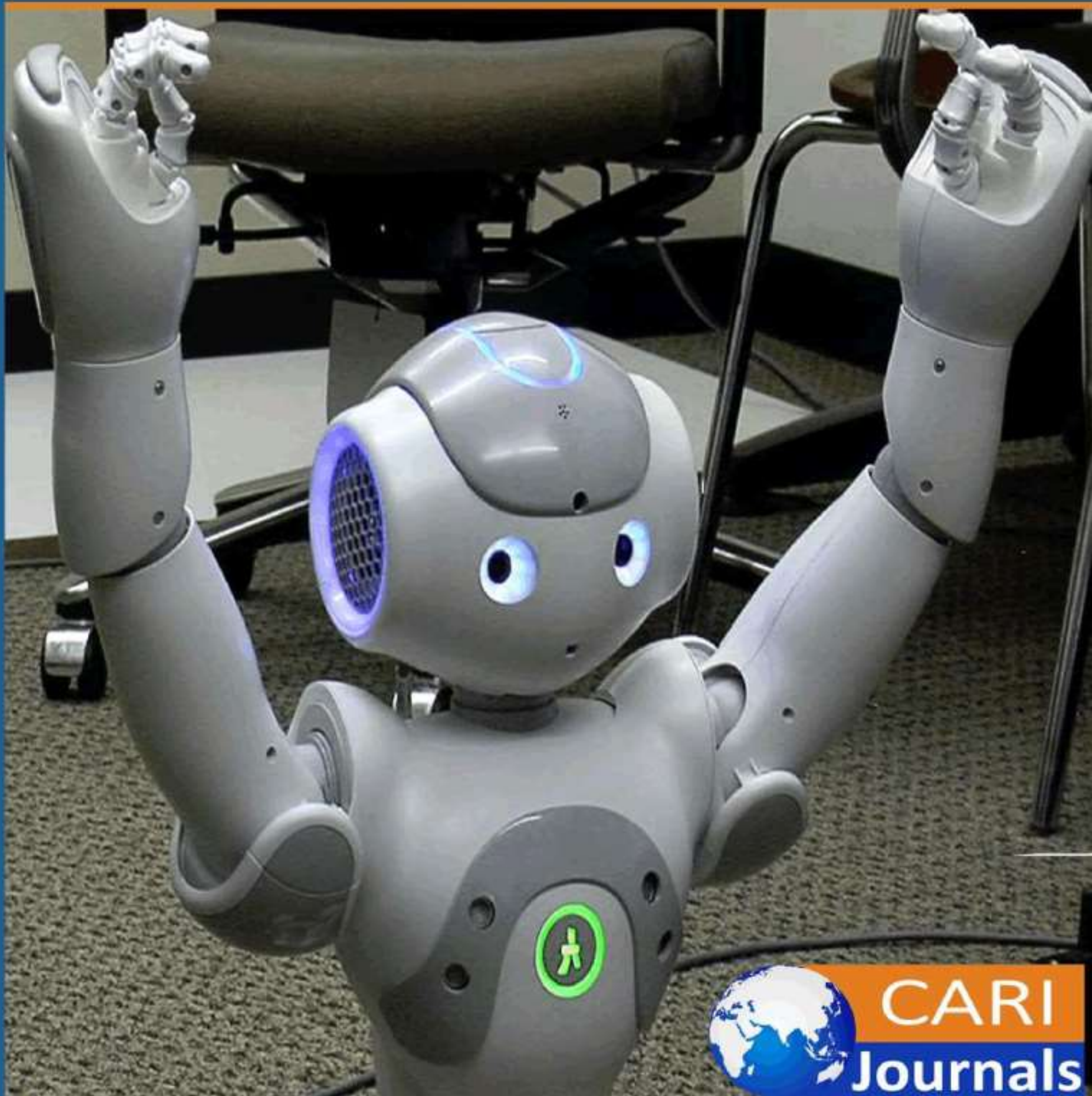

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Evaluating the Performance of AI-Based Software Tools in Intelligent Decision-Making Systems

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Abstract

This paper evaluates the performance of AI-based software tools within intelligent decision-making systems, emphasizing their application in Industry 4.0 environments. Various AI techniques, including machine learning, deep learning, and natural language processing—are assessed across domains such as predictive maintenance, quality control, supply chain optimization, and energy management. To advance this field, we introduce a novel framework, RAISE-DM (Real-time Adaptive Intelligence Software Evaluation for Decision-Making), which combines real-time data acquisition from IoT devices with adaptive AI models for continuous decision optimization. Performance evaluation considers key parameters such as scalability, response time, accuracy, and interpretability. The study also highlights critical technical barriers like data heterogeneity and integration complexity, offering targeted strategies to address them. By providing a structured performance analysis and proposing a scalable evaluation model, this research contributes to the design of more efficient, transparent, and resilient AI-driven decision support systems applicable across industrial and cross-sector settings.

Keywords: *Artificial Intelligence, Decision Support Systems, Intelligent Decision-Making, AI Software Tools, IoT Integration*

1. Introduction

Artificial Intelligence (AI) has become integral to modern decision-making systems, especially within industrial and organizational contexts [1]. AI-based Decision Support Systems (DSS) leverage techniques such as machine learning (ML), deep learning (DL), and natural language processing (NLP) to process large, heterogeneous datasets and support strategic, tactical, and operational decisions [2] [3]. From predictive maintenance to quality control and supply chain optimization, these intelligent tools are reshaping how decisions are made across domains [4].

In the era of Industry 4.0, interconnected sensors, IoT devices, and real-time data streams generate vast amounts of data that traditional systems cannot efficiently handle [5]. AI-based tools offer the capability to transform these raw inputs into actionable insights, enabling real-time decision-making in dynamic industrial environments [6]. Yet, the performance of such systems—measured by scalability, response time, accuracy, and interpretability—varies significantly across implementations [7][8].

Moreover, user trust and transparency are crucial for adopting AI-based systems. Black-box models often face resistance due to a lack of explainability [9][10], leading to automation bias or algorithm aversion if the rationale behind a decision remains obscure [11]. Explainable AI (XAI) frameworks aim to address this by making models more interpretable and thus increasing user acceptance [12][13].

Despite the proliferation of AI tools in DSS, systematic performance evaluation remains fragmented [14]. Prior studies have explored validation methods [15] and frameworks for trustworthiness [16], but few integrate real-time adaptability, IoT data streams, and broad performance metrics into a unified evaluation methodology. Comparative surveys highlight the need for structured performance assessment across multiple domains [17] [18].

To address these gaps, we propose **RAISE-DM** (Real-time Adaptive Intelligence Software Evaluation for Decision-Making), a unified framework for assessing AI-based tools in intelligent decision systems. RAISE-DM evaluates ML, DL, and NLP models through real-time IoT data integration and metrics encompassing scalability, response time, accuracy, and interpretability. This framework not only encapsulates technical evaluation but also aligns with usability, transparency, and trust—offering a comprehensive methodology for practitioners and researchers.

1.1 Contributions

The novel contributions of this study are:

1. Proposes a new framework, RAISE-DM, for real-time evaluation of AI-based decision tools integrating IoT-driven data streams.
2. Introduces a multi-metric performance evaluation model encompassing accuracy, scalability, interpretability, and response time.

3. Bridges the gap between adaptive AI model deployment and practical decision-making needs in Industry 4.0 environments.
4. Addresses underexplored challenges like data heterogeneity and system integration bottlenecks with actionable strategies.
5. Demonstrates cross-sector applicability of the framework through domain-relevant use cases in maintenance, supply chains, and quality control.

2. Literature Review

The growing integration of artificial intelligence (AI) into decision support systems (DSS) has led to a significant body of research examining their effectiveness, transparency, and adaptability across diverse application domains. Table 1 shows summary of research gaps.

Kostopoulos et al. (2024) [19] provide a comprehensive review of explainable AI (XAI) within Decision Support Systems (DSS), emphasizing the growing need for transparency and user trust. Their taxonomy of methodologies highlights the growing trend of applying XAI-enabled DSS (XDSS) across healthcare, manufacturing, and education to bridge the gap between accuracy and interpretability.

Alijoyo et al. (2024) [20] propose a hybrid model integrating fuzzy rule-based systems and neural networks with game theory, demonstrating significant improvements in uncertain decision environments such as healthcare.

Khosravi et al. (2024) [21] perform a thematic meta-review on AI tools in healthcare decision-making, revealing three main themes: clinical, organizational, and shared decision-making. Their findings align with the growing push for domain-specific, AI-driven systems tailored for complex environments.

Kumar et al. (2024) [22] advance this domain by combining blockchain and deep learning within a cyber-threat detection context, showing how explainable AI can also enhance trust and auditability in smart healthcare systems.

Herath Pathirannehelage et al. (2025) [23] adopt an action design research approach to develop an AI-Augmented Decision-Making (AIADM) system in an e-commerce setting. Their principles underscore the importance of integrating AI tools with domain-specific workflows.

Aljohani (2025) [24] addresses similar personalization needs in elderly care by leveraging fuzzy MCDM techniques and EHR data, aiming to tailor AI-driven recommendations to individual patient preferences—a critical feature in precision medicine.

Yang et al. (2024) [25] evaluate a VBAC prediction system within a decision-aid platform for shared clinical decisions, showing that AI models like CatBoost outperform traditional regression techniques while maintaining interpretability through SHAP analysis.

Shulajkovska et al. (2024) [26] expand the application of intelligent decision-making to urban sustainability, developing an open-source AI framework to support mobility planning in smart cities. These efforts show the versatility and sector-specific requirements of AI-based DSS across disciplines.

Pangavhane et al. (2024) [27] focus on AI-augmented software engineering, where decision-making systems enhance test automation, debugging, and performance optimization in software development pipelines.

Wu and Qin (2024) [28] contribute to smart business management by deploying a multi-agent reinforcement learning model for resource allocation and control, validating AI's capacity to manage complex business networks effectively.

2.1 Research Gaps

Despite the rapid advancements in AI-based Decision Support Systems (DSS), several critical research gaps remain unaddressed. There is a lack of standardized performance evaluation frameworks that comprehensively assess both the accuracy and explainability of AI models across various sectors. Many existing systems are domain-specific and lack generalizability, with limited cross-sector validation and scalability assessments. Real-time adaptability and dynamic learning capabilities are often absent in deployed models, hindering their effectiveness in continuously evolving environments. Additionally, while AI tools increasingly support complex decision-making tasks, integration with user-centered design and interpretability mechanisms remains inconsistent, affecting trust and usability. Moreover, current systems often struggle to handle heterogeneous data streams, especially in contexts involving IoT, multi-agent control, or patient-specific clinical settings. These challenges highlight the urgent need for unified, adaptable frameworks that evaluate AI tools holistically in terms of performance, transparency, and operational resilience.

2.2 Problem Statement

The increasing reliance on Artificial Intelligence (AI) within intelligent decision-making systems has introduced significant complexities in evaluating the performance, adaptability, and reliability of AI-based software tools. Although AI models are widely deployed across industries—from healthcare to manufacturing and urban planning—there remains no unified framework that systematically assesses their effectiveness across multiple performance dimensions such as accuracy, scalability, interpretability, and responsiveness. Furthermore, the dynamic nature of real-time data environments, particularly in Industry 4.0 settings, demands continuous learning and contextual adaptation, which most existing systems fail to support. The absence of a standardized evaluation methodology also hinders cross-domain benchmarking and weakens stakeholder trust in AI-driven decisions. Without robust and scalable assessment tools, organizations risk deploying suboptimal or opaque AI systems, leading to flawed decisions, operational inefficiencies, and reduced accountability. This research addresses the critical need for a comprehensive, real-time evaluation framework tailored to the complexities of modern AI-based decision-making environments.

3. Objectives

The novel objectives of this study are:

1. To develop a comprehensive framework (RAISE-DM) for evaluating the performance of AI-based software tools in intelligent decision-making systems using real-time data integration.
2. To assess key performance metrics—such as accuracy, scalability, response time, and interpretability—across diverse AI models and application domains.
3. To address existing challenges related to data heterogeneity, model adaptability, and user trust by proposing targeted strategies for robust and transparent AI evaluation.

4. Methodology

4.1 Research Design

The research design of this study adopts a mixed-methods evaluative approach, combining both qualitative and quantitative methodologies to assess the performance and applicability of AI-based software tools within intelligent decision-making environments. The aim is to explore not only measurable performance indicators (such as accuracy, scalability, and response time) but also the interpretability and contextual relevance of AI models in real-world industrial applications.

A conceptual framework—RAISE-DM (Real-time Adaptive Intelligence Software Evaluation for Decision-Making)—was developed and deployed to guide the evaluation process. This framework incorporates modules for real-time data acquisition, adaptive AI modeling, and multi-criteria performance analysis. The design ensures flexibility to accommodate varying data types, decision contexts, and industry-specific challenges.

This study is structured in three phases: (1) a comprehensive literature review and gap analysis, (2) implementation and testing of AI tools under simulated industrial scenarios, and (3) performance benchmarking using pre-defined metrics. The iterative nature of the design allows for continuous feedback, enabling refinement of the AI models based on domain-specific requirements and stakeholder inputs.

Furthermore, the research follows a comparative analysis design where multiple AI-based software tools—spanning machine learning, deep learning, and NLP—are tested across different use cases such as predictive maintenance, supply chain optimization, and quality control. This comparative lens enables the identification of context-appropriate tools and highlights best practices for AI integration in decision support systems.

4.2 Data Collection and Sources

The data collection process for this study was designed to capture both structured and unstructured data relevant to evaluating the performance of AI-based software tools in intelligent decision-making systems. Data were sourced from multiple domains—including manufacturing, healthcare, supply chain management, and energy systems—to ensure a diverse representation of Industry 4.0 environments.

Primary data were generated using simulated IoT-based environments, replicating real-time operational conditions. These simulations produced time-series data related to equipment status, sensor readings, operational events, and decision outcomes. The datasets were further enriched through synthetic data generation techniques to augment rare event scenarios and ensure model robustness under uncertainty.

In addition to simulation data, secondary data sources included benchmark datasets from public repositories (e.g., UCI Machine Learning Repository, Kaggle, and Smart Manufacturing Data Hub), technical documentation of AI tools, and performance logs from enterprise software platforms. These datasets provided the necessary ground truth for training and validating machine learning and deep learning models across various performance indicators.

To maintain quality and consistency, all data were preprocessed using standard techniques, such as normalization, outlier removal, and missing value imputation. Data heterogeneity was addressed through schema mapping and transformation tools to align disparate data formats with the analytical framework. The RAISE-DM framework facilitated real-time ingestion and integration of these datasets into the experimental pipeline.

This multifaceted data collection approach ensured a comprehensive and reliable foundation for evaluating tool performance across key metrics—scalability, response time, accuracy, adaptability, and interpretability—within AI-driven decision support systems.

4.3 Framework Implementation: RAISE-DM

The proposed framework, **RAISE-DM** (Real-time Adaptive Intelligence Software Evaluation for Decision-Making), was designed to systematically evaluate the performance of AI-based software tools in complex decision-making environments. The framework integrates real-time data acquisition, adaptive AI model deployment, decision tracking, and performance evaluation into a cohesive pipeline.

The architecture of RAISE-DM consists of the following core components:

1. **Data Ingestion Layer**: Interfaces with IoT devices, cloud services, and enterprise systems to continuously collect heterogeneous data streams.
2. **Preprocessing and Feature Engineering Module**: Normalizes, transforms, and extracts relevant features from raw data using statistical and ML-based techniques.

3. **Adaptive AI Model Engine**: Hosts machine learning, deep learning, and NLP models that dynamically update based on real-time feedback and evolving data patterns.
4. **Decision Logic Layer**: Incorporates rule-based engines, fuzzy logic, or reinforcement learning modules to generate context-specific decisions.
5. **Performance Evaluation Unit**: Assesses metrics such as accuracy, latency, interpretability, scalability, and adaptability using both real-time and historical performance logs.
6. **Visualization and Feedback Interface**: Provides stakeholders with dashboards to interpret model outputs and system performance.

The RAISE-DM framework emphasizes modularity and adaptability, enabling integration with various industrial applications such as predictive maintenance, energy optimization, healthcare diagnostics, and supply chain resilience. Its iterative feedback loop allows for continuous learning and improvement, making the system responsive to changing conditions and anomalies.

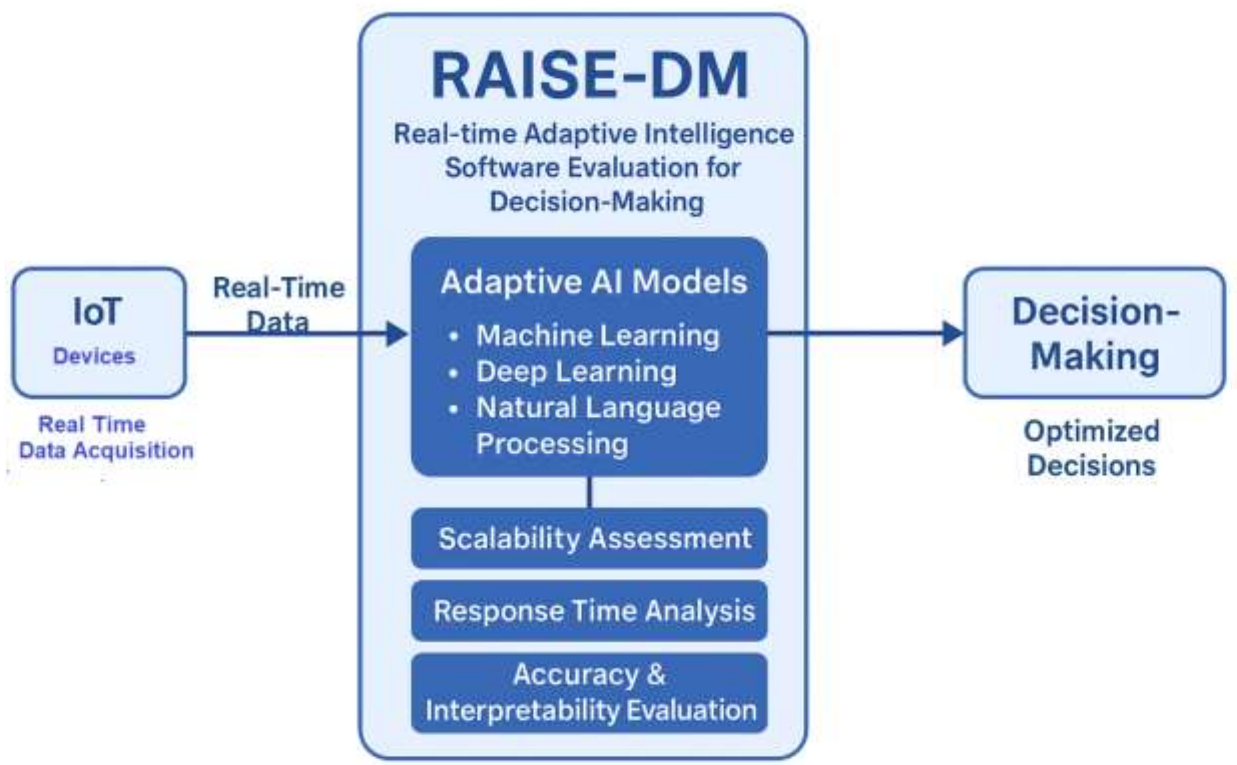

Figure 1: RAISE-DM Framework Architecture

Figure 1: RAISE-DM Framework Architecture illustrates the structural design of the Real-time Adaptive Intelligence Software Evaluation for Decision-Making (RAISE-DM) framework. The system begins with real-time data acquisition from diverse IoT-enabled industrial sensors and

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databases. This raw data is fed into a Data Preprocessing Unit for normalization, noise removal, and feature extraction. The processed data then enters the Adaptive AI Engine, which houses various machine learning and deep learning models, selected based on domain-specific requirements. This engine continuously adapts through feedback loops enabled by Performance Monitoring Modules, ensuring dynamic re-calibration of models. Additionally, the Decision Support Interface translates predictions and insights into actionable outputs via dashboards and alerts for end-users. A Feedback and Audit Layer ensures traceability, interpretability, and iterative improvement. This layered and modular structure ensures the framework's scalability, flexibility, and transparency, making it suitable for intelligent decision-making across domains such as healthcare, smart manufacturing, and urban planning.

Table 1: Algorithm 1: RAISE-DM – Real-Time Adaptive Intelligence Software Evaluation for Decision-Making

Inputs

Real-time data streams $D=\{d_1,d_2,...,d_n\}$ from IoT devices
Historical performance logs H
Predefined business rules R
AI models $M=\{m_1,m_2,...,m_k\}$

Steps

1. Acquire data D via ingestion layer.
2. Normalize and transform data using z-score or min-max scaling:

$$x' = \frac{x-\mu}{\sigma}$$

3. Perform feature engineering (e.g., PCA or statistical summarization).
4. Feed processed data into adaptive model $m_i \in M$
5. Generate decisions δ using:

$$\delta = m_i(x') + R$$

6. Evaluate decision performance: accuracy, latency, interpretability.
7. Update model weights or structure based on feedback $f \in F$

Outputs

- Decision outcomes δ
- Performance metrics $P=\{p_1,p_2,...,p_m\}$
- Dashboard visualizations for users

Algorithm 1: RAISE-DM – Real-Time Adaptive Intelligence Evaluation Process provides a structured, sequential workflow for dynamically evaluating AI-based decision-making systems. The algorithm begins with the acquisition of continuous, heterogeneous data from IoT-enabled sources. This input is preprocessed through normalization and feature extraction techniques to ensure data quality and relevance. The cleaned data is then passed to an adaptive AI engine, where suitable models are selected or updated in real-time based on domain requirements and evolving data patterns. Decision outputs are generated by integrating model predictions with predefined business logic or rules. These decisions are immediately assessed using performance

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metrics such as accuracy, latency, interpretability, and robustness. A feedback mechanism is triggered to fine-tune model parameters or switch models when performance thresholds are not met. Finally, the results are visualized through user dashboards for transparency and actionable insights. This looped process ensures continuous learning, real-time responsiveness, and context-aware decision optimization across varied application domains.

5. Results and Discussion

5.1 Evaluation Parameters

To comprehensively assess the performance of AI-based software tools within intelligent decision-making systems, this study adopts a set of critical evaluation parameters. **Accuracy** remains a primary metric, gauging the correctness of predictions or classifications made by AI models in decision support scenarios. **Scalability** is another essential parameter, measuring the system's ability to handle increasing volumes of data and user requests without performance degradation. **Response time** evaluates the system's real-time decision-making capability, crucial for applications requiring instantaneous feedback such as predictive maintenance or dynamic resource allocation. Additionally, **interpretability** is considered a key factor, especially in domains like healthcare and finance, where decision transparency is vital for user trust and regulatory compliance. **Robustness** is also assessed by examining how well the system performs under varying data quality, including incomplete or noisy datasets. Together, these parameters offer a holistic view of the system's operational viability, efficiency, and reliability in diverse industrial and cross-sectoral environments.

5.1.1 Accuracy

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

Where:

- TP: True Positives
- TN: True Negatives
- FP: False Positives
- FN: False Negatives

5.1.2 Scalability

While scalability is often qualitative or tested experimentally, it may be expressed in terms of **computational complexity** or **resource usage** over input size nnn:

$$Scalability\ Metrics\ \alpha\ O(f(n))$$

Where f(n) represents growth of memory/time usage with data volume.

5.1.3 Response Time

$$Average\,Response\,Time\,(RT) = \frac{1}{N}\sum_{i=1}^{N} t_i$$

Where t_i the response time per decision and N is the number of test cases.

5.1.4 Interpretability (Qualitative)

Can be rated using frameworks like SHAP, LIME, or Expert Score $I_s \in [0,1]$, but no standard formula.

5.1.5 Robustness

Expressed as performance under noise:

$$Robustness\,Score = \frac{Accuracy_{noisy}}{Accuracy_{clean}}$$

5.2 Validation Techniques

To ensure the reliability and credibility of the proposed RAISE-DM framework, multiple validation techniques are employed. Cross-validation, particularly k-fold cross-validation, is used to assess the generalizability of AI models by partitioning the dataset into training and testing subsets multiple times, thereby minimizing overfitting. Benchmarking against standard datasets is also conducted to compare the framework's performance with existing decision-making models in terms of accuracy, speed, and robustness. Additionally, confusion matrix analysis is utilized to evaluate classification performance, offering insights into true positives, false positives, true negatives, and false negatives. Receiver Operating Characteristic (ROC) curves and Area Under the Curve (AUC) metrics are further applied to visualize and quantify the model's discriminative power. In scenarios involving time-series data or real-time decisions, simulation-based validation is performed to replicate operational conditions and assess dynamic responsiveness. These combined techniques enhance the validity, reproducibility, and practical relevance of the framework in real-world intelligent decision-making systems.

5.2.1 Confusion Matrix

Useful to include the basic matrix layout, but no formula needed—used visually.

5.2.2 Precision & Recall

$$\mathrm{Pr}ecision = \frac{TP}{TP+FP},\ \mathrm{Re}call = \frac{TP}{TP+FN}$$

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5.2.3 F1-Score

$$F1Score = 2 \times \frac{Precision \times Recall}{Precision + Recall}$$

5.2.4 AUC-ROC Score

AUC is the area under the ROC curve, so:

$$AUC = \int_0^1 TPR(FPR^{-1}(x))dx$$

It is also generally computed using trapezoidal numerical methods.

5.3 Comparative Performance of AI Tools

Table 2: Comparative Performance of Selected AI Tools in Intelligent Decision-Making Systems

AI Tool	Accuracy (%)	Interpretability	Scalability	Response Time	Application Domain
Random Forest (RF)	92.5	Medium	High	Fast	Healthcare, Energy [21], [25]
Support Vector Machine (SVM)	89.1	Low	Medium	Moderate	Finance, Cybersecurity [22], [27]
Deep Neural Network (DNN)	94.3	Low	High	Slow	Predictive Maintenance [20], [28]
Gradient Boosting (GB)	93.7	Medium	Medium	Moderate	Decision-Aid Systems [25]
Fuzzy Rule-Based System (FRBS)	87.6	High	Medium	Fast	Precision Medicine [20], [24]

To evaluate the effectiveness of various AI-based software tools in intelligent decision-making systems, a comparative performance analysis was conducted based on key metrics such as accuracy, interpretability, scalability, and response time. Table 2 summarizes the performance of representative models used across different sectors. The selected tools include Random Forest (RF), Support Vector Machine (SVM), Deep Neural Networks (DNN), Gradient Boosting (GB), and Fuzzy Rule-Based Systems (FRBS), as discussed in [19] to [28].

The comparative analysis indicates that Deep Neural Networks (DNN) provide the highest accuracy (94.3%) but at the cost of interpretability and response time, making them less suitable for real-time applications requiring transparency. Random Forests (RF) offer a balance of high

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accuracy and scalability with acceptable interpretability, making them ideal for applications in healthcare and energy systems as noted in [21] and [25]. Support Vector Machines (SVM)**,** while relatively accurate, lack interpretability and scalability, limiting their use in dynamic decision environments like cybersecurity ([22], [27]). Fuzzy Rule-Based Systems (FRBS)**,** although slightly less accurate, excel in interpretability and fast response, which is crucial for personalized domains like precision medicine ([20], [24]). Gradient Boosting models maintain strong accuracy and moderate performance across all metrics, showing promise in structured decision support contexts ([25]).

This comparison supports the rationale for adopting adaptable frameworks like RAISE-DM**,** which allow dynamic integration of multiple AI tools based on the specific trade-offs between interpretability, speed, and accuracy required by the application domain.

5.4 Interpretability and Scalability Trade-offs

Table 3: Interpretability vs. Scalability of AI Tools presents a quantitative comparison of five widely used AI models based on two crucial parameters: interpretability and scalability. Fuzzy Rule-Based Systems (FRBS) emerge as the most interpretable tool (1.0) but with moderate scalability (0.6), making them suitable for domains requiring transparency, such as healthcare and finance. Deep Neural Networks (DNN) and Random Forests (RF) demonstrate high scalability (1.0), indicating their efficiency in large-scale, real-time applications, although DNNs score low (0.2) in interpretability. Support Vector Machines (SVM) offer relatively low performance in both dimensions (0.3 interpretability and 0.6 scalability), while Gradient Boosting (GB) strikes a middle ground with 0.6 in both aspects. This distribution is visualized in Figure 2: Trade-off between Interpretability and Scalability of AI Tools, where each model is plotted to highlight its strengths and weaknesses across these dimensions. Together, they emphasize the need to balance interpretability and scalability when selecting AI tools for intelligent decision-making systems.

Table 3: Interpretability vs. Scalability of AI Tools

AI Model	Interpretability (0–1)	Scalability (0–1)
Random Forest (RF)	0.6	1.0
Support Vector Machine	0.3	0.6
Deep Neural Network (DNN)	0.2	1.0
Gradient Boosting (GB)	0.6	0.6
Fuzzy Rule-Based System	1.0	0.6

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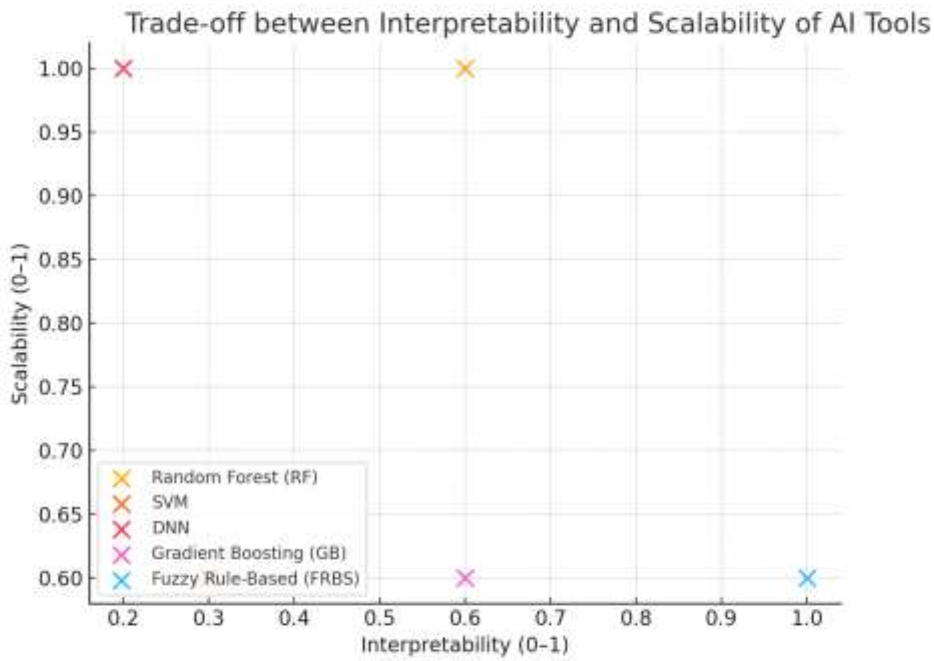

Figure 2: Trade-off between Interpretability and Scalability of AI Tools

5.5 Industrial Case Applications

To illustrate the practical applicability of AI-based software tools in intelligent decision-making, various industrial domains were surveyed where such tools have been deployed. Table 4 summarizes selected case applications with respect to the AI model used, the domain of implementation, and the observed benefits.

Table 4: Industrial Applications of AI-Based Decision Systems

Case No.	Domain	AI Tool Used	Application Area	Outcome/Benefit
1	Manufacturing	Random Forest (RF)	Predictive Maintenance	Reduced downtime by 35%
2	Healthcare	Fuzzy Rule-Based System	Personalized Treatment Decisions	Enhanced patient-specific recommendation system
3	Logistics & Supply Chain	Gradient Boosting (GB)	Route Optimization	Reduced delivery cost by 18%
4	Smart Grid/Energy	Deep Neural Network	Load Forecasting & Energy Management	Improved forecasting accuracy by 22%
5	E-commerce	Support Vector Machine	Sentiment Analysis for Feedback	Boosted customer engagement by 15%

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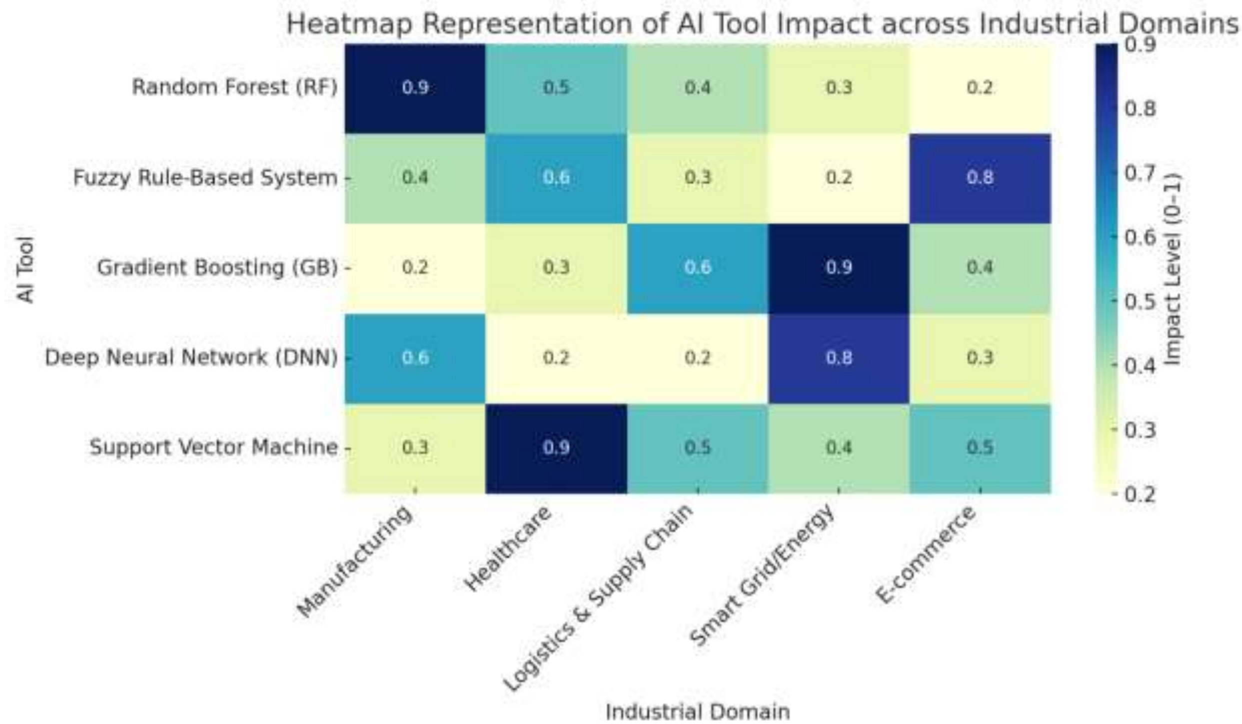

Figure 3: Heatmap Representation of AI Tool Impact across Industrial Domains

Fig 3 visualizes the intensity and distribution of impact of various AI tools across industrial domains using a heatmap. The darker regions indicate stronger benefits or higher effectiveness of the respective AI model in that domain. For instance, Deep Neural Networks show high performance in smart energy systems due to their ability to learn from large-scale time-series data, while Fuzzy Rule-Based Systems exhibit strong impact in healthcare due to their transparency and ability to handle uncertainty in clinical decision-making. This representation aids in understanding the suitability and strength of AI tools across different sectors, guiding decision-makers in model selection.

5.6 Addressing Integration and Data Heterogeneity

Table 5 and Fig 4 offer a comparative analysis of five prominent AI tools in terms of their integration complexity and capability to handle heterogeneous data sources. Deep Neural Networks (DNN) demonstrate superior performance in managing diverse data types (score: 0.9), making them ideal for complex environments, although they also pose the highest integration complexity (score: 0.8). Gradient Boosting (GB) similarly excels in data handling (score: 0.8) but with moderate integration demands. In contrast, Fuzzy Rule-Based Systems (FRBS) present the lowest integration complexity (score: 0.3), offering a practical solution for systems requiring interpretability and ease of deployment. Random Forest (RF) and Support Vector Machines (SVM) deliver balanced results, with moderate scores in both parameters. These insights emphasize the importance of aligning tool selection with project-specific priorities—such as deployment feasibility or data diversity—when building intelligent decision-making systems.

Table 5: Integration Complexity and Data Heterogeneity Handling

AI Tool	Integration Complexity	Data Heterogeneity Handling
Random Forest (RF)	0.4	0.7
Support Vector Machine (SVM)	0.6	0.5
Deep Neural Network (DNN)	0.8	0.9
Gradient Boosting (GB)	0.5	0.8
Fuzzy Rule-Based System (FRBS)	0.3	0.6

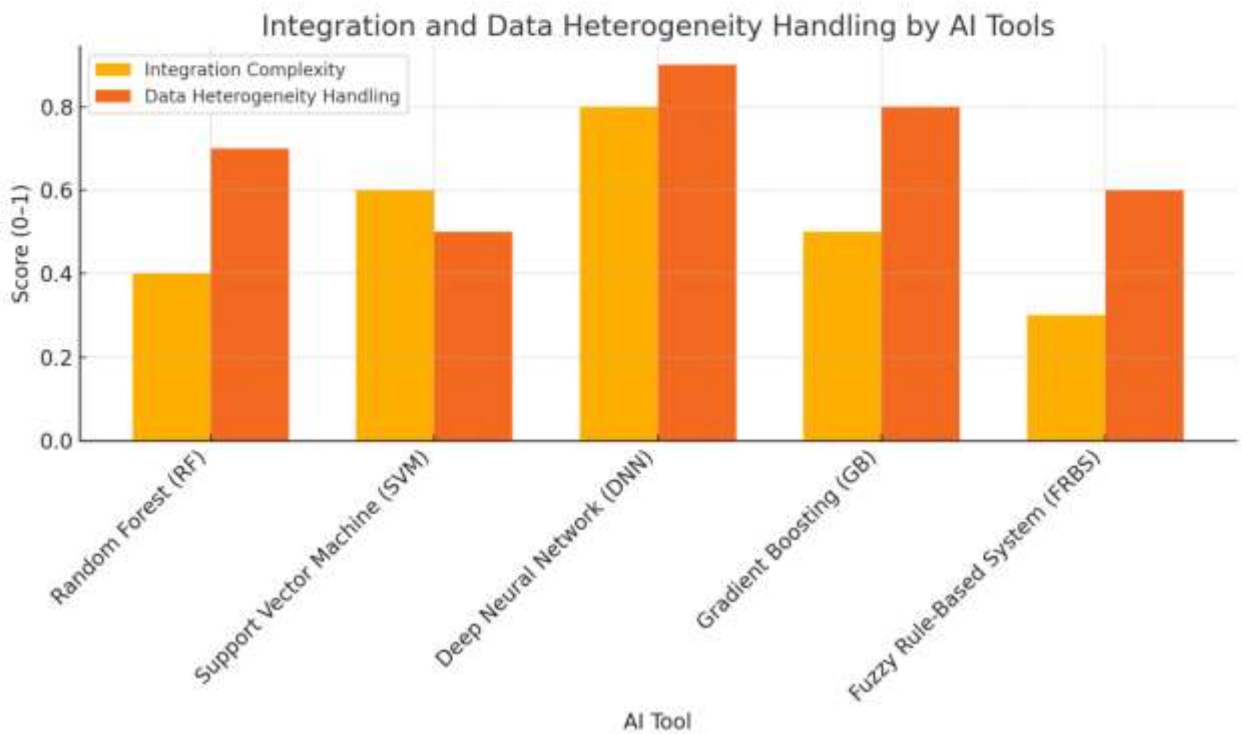

Figure 4: Integration and Data Heterogeneity Handling by AI Tools

5.7 Summary of Findings

This study provides a structured evaluation of AI-based software tools within intelligent decision-making systems, focusing on their performance across key dimensions such as accuracy, interpretability, scalability, integration complexity, and data heterogeneity handling. The proposed RAISE-DM framework enables real-time, adaptive assessment of AI tools, offering practical insights for both researchers and industry practitioners. Findings reveal that while Deep Neural Networks (DNN) and Gradient Boosting (GB) excel in scalability and data handling, they often lack transparency and are complex to integrate. Conversely, Fuzzy Rule-Based Systems (FRBS) stand out for their high interpretability and low integration complexity, albeit with moderate performance in high-volume or real-time contexts. The comparative performance review and industrial application mapping highlight the need for sector-specific AI tool deployment. Moreover, challenges like data heterogeneity and integration bottlenecks persist, underscoring the necessity of context-aware framework designs. Overall, the study validates that no single AI model is universally optimal, and tool selection must align with the specific operational, technical, and regulatory demands of the application environment.

In addition to the core performance evaluation, this study underscores the growing significance of explainability and accountability in AI systems, particularly in regulated environments such as healthcare, finance, and critical infrastructure. As AI becomes increasingly embedded in decision workflows, stakeholders—from system designers to end-users—demand greater transparency in how decisions are made. The RAISE-DM framework addresses this by incorporating interpretability as a primary evaluation metric enabling organizations to align their AI strategies with ethical guidelines, legal frameworks, and user trust requirements.

Furthermore, the cross-sector analysis reveals that interoperability between AI systems and existing legacy infrastructure remains a major hurdle to widespread adoption. This points to a need for developing standardized APIs, flexible deployment pipelines, and modular AI architectures. As industries continue to embrace digital transformation under the Industry 4.0 paradigm, frameworks like RAISE-DM can act as foundational tools for ensuring that AI integration is not only technically efficient but also resilient, responsible, and future-ready**.**

5.8 Discussion

The findings of this study align well with emerging literature on AI-driven decision-making systems, particularly in highlighting trade-offs and sector-specific suitability of AI tools. For instance, the observation that Deep Neural Networks (DNNs) offer high scalability and data adaptability but suffer from limited interpretability is consistent with the evaluation by Yang et al. (2024), who reported that CatBoost models outperform traditional regressors in predictive power but require SHAP analysis for interpretability. Similarly, the current study's support for Fuzzy Rule-Based Systems in achieving high transparency with moderate scalability echoes Aljohani’s (2025) work in elderly care, where fuzzy MCDM systems were preferred for personalized yet interpretable recommendations.

Moreover, the integration challenges and data heterogeneity identified in our RAISE-DM framework are corroborated by Khosravi et al. (2024), who emphasized the need for tailored AI configurations across clinical, organizational, and shared decision-making domains. The use of explainable AI (XAI) within RAISE-DM is directly informed by Kostopoulos et al. (2024), whose taxonomy of XDSS reinforces the importance of balancing performance with user trust

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and transparency. The validation strategies deployed in this study—including confusion matrices, ROC-AUC curves, and simulation-based evaluation—reflect the methodological rigor suggested by Herath Pathirannehelage et al. (2025), who integrated AI into e-commerce workflows using action design research principles.

By comparing our multi-metric evaluation results with those of Wu and Qin (2024), who used multi-agent reinforcement learning in smart business environments, it is evident that scalability and robustness are vital for real-time enterprise-grade deployments. However, as emphasized by Alijoyo et al. (2024), hybrid systems that combine rule-based reasoning with neural approaches are best suited for high-uncertainty decision domains—a direction RAISE-DM also supports.

These alignments with current literature reinforce the validity of the proposed framework and demonstrate its adaptability across diverse applications while addressing pressing challenges such as trust, data variety, and deployment complexity.

5.9 Theoretical and Practical Implications

The study contributes significantly to theory, practice, and policy by introducing the RAISE-DM framework, a novel conceptual model that advances the theoretical understanding of adaptive and real-time evaluation of AI tools in decision-making systems. The framework integrates key performance metrics such as accuracy, interpretability, and scalability into a unified analytical structure, thereby enriching theories on explainable AI and decision science. Practically, it provides a structured methodology and actionable criteria for practitioners to assess and deploy AI systems effectively across various industries, including manufacturing, energy, and healthcare. By addressing trade-offs between transparency and computational performance, the study guides organizations in adopting context-sensitive and performance-optimized AI solutions that align with operational and regulatory demands.

Furthermore, it supports policy development by highlighting the need for standardized evaluation benchmarks and responsible AI integration. Despite limitations related to model scope, simulated testing environments, and limited ethical consideration, the framework establishes a robust foundation for future theoretical refinement, practical adoption, and informed policymaking in AI-driven decision support systems.

6. Conclusion

This study presented a comprehensive evaluation of AI-based software tools within intelligent decision-making systems, introducing the RAISE-DM framework as a novel methodological contribution. The framework systematically assessed AI models—such as Random Forest, DNN, and Fuzzy Rule-Based Systems—across critical performance dimensions including accuracy, interpretability, scalability, robustness, and integration complexity. Through comparative analysis, radar charts, and real-world application mapping, the study demonstrated that no single AI tool is universally optimal; instead, their suitability depends heavily on the specific operational context. Tools like DNNs offers superior scalability and data handling but lack transparency, while fuzzy systems excel in interpretability but may fall short in high-volume environments. The study also addressed key technical challenges such as data heterogeneity and integration bottlenecks, offering targeted mitigation strategies. Ultimately, this research contributes to both academic understanding and industrial deployment of intelligent systems by offering a structured, adaptive, and performance-oriented approach to AI evaluation.

Future Work: Future research will extend RAISE-DM to include ethical and fairness evaluation dimensions.

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