



## Integrating Decision Intelligence and Business Rules Management for Enterprise Applications

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**ABSTRACT:** Decision-making is a critical component of enterprise applications, influencing operational efficiency, business performance, and strategic outcomes. With the increasing complexity of business environments and the growth of data-driven processes, traditional decision-making approaches are no longer sufficient. Decision Intelligence (DI) has emerged as an advanced paradigm that combines data analytics, artificial intelligence, and decision modeling to support intelligent and automated decision-making. At the same time, Business Rules Management Systems (BRMS) provide a structured approach to defining, managing, and executing business rules within enterprise systems. This paper presents an integrated framework that combines Decision Intelligence and BRMS to enhance enterprise decision-making capabilities. The proposed system leverages data analytics, machine learning techniques, and rule-based logic to provide accurate, consistent, and scalable decision support. The architecture, methodology, and implementation aspects of the integrated system are discussed in detail. Experimental evaluation demonstrates improved decision accuracy, flexibility, and efficiency compared to standalone systems. The study highlights the potential of combining DI and BRMS to enable intelligent, adaptive, and automated enterprise applications [1], [3], [5].

**KEYWORDS:** Decision Intelligence, Business Rules Management System, Enterprise Applications, Artificial Intelligence, Decision Support Systems

### I. INTRODUCTION

Modern enterprise applications operate in highly dynamic, competitive, and data-driven environments where effective and timely decision-making is essential for achieving organizational goals and maintaining a competitive advantage. With the rapid growth of digital transformation, businesses are generating and processing vast volumes of structured and unstructured data from multiple sources such as transactional systems, customer interactions, social media, and external market data. This increasing complexity requires advanced decision-making capabilities that can analyze large datasets, identify meaningful patterns, and provide actionable insights in real time. However, traditional decision-making approaches, which are often based on static rules, manual analysis, and predefined workflows, are becoming increasingly inadequate for handling complex and rapidly changing business scenarios [1], [2].

In response to these challenges, Decision Intelligence (DI) has emerged as a powerful and comprehensive approach that integrates data science, artificial intelligence, machine learning, and decision theory to improve the quality and effectiveness of decision-making processes. DI enables organizations to transform raw data into valuable insights, predict future outcomes, and automate decision-making using advanced analytical models and algorithms. By leveraging predictive analytics and data-driven techniques, DI helps organizations optimize operations, reduce risks, and enhance strategic planning [3], [4]. Moreover, DI supports continuous learning and improvement, allowing enterprise systems to adapt dynamically to evolving business conditions.

At the same time, Business Rules Management Systems (BRMS) play a critical role in enterprise applications by providing a structured and systematic approach to defining, managing, and executing business rules. BRMS enables organizations to separate business logic from application code, making it easier to update rules, ensure compliance with regulations, and maintain consistency in decision-making processes. This flexibility allows enterprises to quickly respond to changes in policies, market conditions, and regulatory requirements without significant system modifications [5], [6]. As a result, BRMS has become a key component in enterprise systems for ensuring governance, transparency, and control over decision logic.



Despite their individual strengths, standalone DI and BRMS solutions have certain limitations. Decision Intelligence systems, while powerful in predictive analytics and data-driven insights, may lack transparency and explicit control over decision logic, making it difficult for organizations to ensure compliance and interpretability. On the other hand, BRMS solutions, although highly effective in managing rule-based decisions, may not fully utilize the potential of advanced analytics and machine learning for handling complex and data-intensive scenarios. These limitations highlight the need for a unified approach that combines the strengths of both paradigms.

Integrating Decision Intelligence with Business Rules Management Systems offers a promising solution for developing intelligent, adaptive, and scalable enterprise applications. Such integration enables organizations to combine predictive analytics with rule-based governance, resulting in more accurate, consistent, and explainable decision-making processes. It also facilitates the automation of complex decisions while maintaining transparency and compliance, which are critical in modern business environments.

This paper proposes an integrated framework that combines Decision Intelligence and BRMS to enhance enterprise applications. The proposed system leverages data analytics, machine learning models, and rule-based logic to support intelligent and automated decision-making. The framework is designed to improve decision accuracy, consistency, scalability, and adaptability, while also addressing challenges related to transparency and governance. The study aims to demonstrate how the integration of DI and BRMS can provide a robust foundation for next-generation enterprise systems capable of handling complex and dynamic business requirements.

## II. LITERATURE REVIEW

In recent years, there has been a growing interest in enhancing enterprise decision-making through the integration of data-driven analytics and rule-based systems. Organizations are increasingly relying on intelligent technologies to manage complex decision processes, improve operational efficiency, and gain competitive advantages. Decision Intelligence (DI) has emerged as a key paradigm in this domain, enabling organizations to combine data analytics, artificial intelligence, and decision modeling to support strategic and operational decision-making. Several studies have demonstrated that DI can significantly improve business performance by enabling predictive insights, optimizing workflows, and supporting data-driven strategies [3], [7].

Machine learning and artificial intelligence techniques have been widely adopted in enterprise systems for predictive analytics and automation. These techniques have been successfully applied in various business applications, including demand forecasting, fraud detection, risk assessment, and customer behavior analysis. By analyzing large volumes of historical and real-time data, machine learning models can identify patterns, trends, and anomalies, providing valuable insights that support proactive decision-making [8], [9]. However, despite their effectiveness, these approaches often face challenges related to transparency, interpretability, and governance. The “black-box” nature of many machine learning models makes it difficult for organizations to understand and justify decisions, which can limit their adoption in critical business environments.

Business Rules Management Systems (BRMS) have been widely used in enterprise applications to address the need for transparency, control, and consistency in decision-making. BRMS allows organizations to define, manage, and execute business rules separately from application logic, enabling greater flexibility and easier maintenance. These systems play a crucial role in ensuring compliance with regulatory requirements and maintaining standardized decision processes across the organization [5], [10]. By providing clear and interpretable rule-based logic, BRMS enhances the reliability and accountability of enterprise decisions. However, traditional rule-based systems are limited in their ability to handle large-scale data, adapt to changing conditions, and incorporate predictive insights, which restricts their effectiveness in dynamic business environments.

To overcome these limitations, several studies have explored hybrid approaches that integrate machine learning with rule-based systems. These approaches aim to combine the predictive capabilities of machine learning with the transparency and governance provided by rule-based systems. For example, machine learning models can be used to generate predictions, which are then validated or refined using predefined business rules. This combination enhances decision accuracy while ensuring compliance and interpretability [11], [12]. Hybrid models have shown promising results in improving decision-making performance across various enterprise applications.

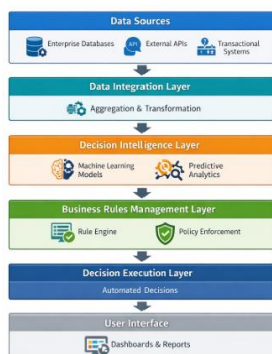


Despite these advancements, significant challenges remain in the development and deployment of integrated decision systems. System integration is a major concern, as combining different technologies such as machine learning platforms and BRMS requires compatibility, interoperability, and efficient data exchange mechanisms. Scalability is another critical issue, particularly when dealing with large and continuously growing datasets in enterprise environments. Additionally, interpretability and trust remain key challenges, as organizations require clear explanations of how decisions are made, especially in high-stakes scenarios [13].

Overall, the existing literature highlights the potential benefits of integrating Decision Intelligence and BRMS but also reveals gaps related to system integration, scalability, and explainability. These gaps emphasize the need for a unified and robust framework that effectively combines data-driven analytics with rule-based governance. This study addresses these challenges by proposing an integrated DI-BRMS framework designed to enhance decision-making capabilities in enterprise applications.

### III. SYSTEM ARCHITECTURE

The proposed system architecture integrates Decision Intelligence (DI) and Business Rules Management Systems (BRMS) into a unified and scalable framework designed to support intelligent, data-driven, and rule-governed decision-making in enterprise applications. The architecture follows a layered approach, where each layer performs a specific function while interacting seamlessly with other components. This modular design ensures flexibility, scalability, and ease of integration with existing enterprise systems.



**Figure 1:** Integrated Architecture of Decision Intelligence and Business Rules Management System

#### 3.1 Data Integration Layer

The Data Integration Layer is responsible for collecting and consolidating data from multiple heterogeneous sources within the enterprise environment. These sources include enterprise databases, transactional systems, and external APIs that provide real-time or batch data inputs. The collected data may consist of structured data (e.g., relational databases), semi-structured data (e.g., JSON/XML), and unstructured data (e.g., logs or text). Data aggregation and transformation processes are applied to convert the data into a unified format suitable for further analysis. This layer ensures data consistency, completeness, and accessibility, which are critical for accurate decision-making.

#### 3.2 Analytics and Decision Intelligence Layer

The Analytics and Decision Intelligence Layer form the core of the system, where advanced data analysis and predictive modeling are performed. This layer utilizes machine learning models to analyze historical and real-time data, identify patterns, and generate predictive insights. Techniques such as classification, regression, clustering, and anomaly detection are applied depending on the use case. Predictive analytics helps forecast future outcomes, while data mining techniques uncover hidden relationships within the data. This layer enables data-driven decision-making by providing actionable insights that support business processes and strategic planning.

#### 3.3 Business Rules Management Layer

The Business Rules Management Layer is responsible for defining, managing, and executing business rules that govern enterprise decision-making processes. This layer includes a rule repository where business rules are stored and maintained, allowing easy modification and version control. The rule engine executes these rules by evaluating conditions



and triggering appropriate actions. Policy enforcement mechanisms ensure that all decisions comply with organizational policies, regulatory requirements, and business constraints. By separating business logic from application code, this layer enhances flexibility, transparency, and maintainability.

### 3.4 Decision Execution Layer

The Decision Execution Layer integrates outputs from the Decision Intelligence and BRMS layers to perform automated decision-making. This layer combines predictive insights generated by machine learning models with rule-based logic to produce final decisions. It also supports workflow integration, enabling seamless incorporation of decision outcomes into enterprise processes such as order processing, risk management, and customer engagement. Real-time decision support capabilities allow the system to respond quickly to changing conditions, ensuring timely and effective actions.

### 3.5 User Interface Layer

The User Interface Layer provides an interactive platform for end-users, including business analysts, managers, and decision-makers. This layer includes dashboard visualization tools that present key insights, trends, and performance metrics in an intuitive manner. Reporting tools generate detailed reports for analysis and auditing purposes, while decision monitoring features allow users to track and evaluate system decisions over time. The interface is designed to enhance usability and support informed decision-making by providing clear and actionable information.

## IV. METHODOLOGY

The methodology of the proposed integrated Decision Intelligence (DI) and Business Rules Management System (BRMS) framework follows a structured approach that includes data preparation, model development, rule integration, and performance evaluation. This systematic process ensures that the system delivers accurate, reliable, and scalable decision-making capabilities for enterprise applications.

### 4.1 Data Preparation

Data preparation is a critical step in building an effective decision intelligence system. In this study, data is collected from various enterprise sources, including transactional databases, customer relationship management systems, and external data providers. Since enterprise data is often heterogeneous and may contain inconsistencies, preprocessing techniques are applied to ensure data quality and consistency. Data cleaning is performed to remove duplicates, errors, and irrelevant records. Normalization techniques are used to scale numerical features into a consistent range, improving model performance and convergence. Feature engineering is applied to extract meaningful attributes and enhance the predictive power of the dataset. These steps ensure that the data is well-structured and suitable for machine learning and rule-based processing.

### 4.2 Model Development

In the model development phase, machine learning models are designed and trained to support predictive decision-making. These models analyze historical and real-time data to identify patterns, trends, and relationships that can inform future decisions. Common techniques such as classification, regression, and clustering are employed depending on the application requirements. The developed models generate predictive outputs such as risk scores, probability estimates, or recommended actions. These outputs are then used as inputs for the rule-based system, ensuring that predictive insights are aligned with business policies and constraints. The integration of machine learning models enhances the system's ability to handle complex and data-intensive decision scenarios.



Figure 2: Workflow of Hybrid Decision Intelligence and BRMS Integration



### 4.3 Rule Integration

Rule integration is a key component of the proposed framework, where business rules defined in the BRMS are combined with machine learning outputs to create hybrid decision models. Business rules are defined using a rule engine and stored in a centralized repository, allowing easy modification and management. These rules are used to validate, refine, or override the predictions generated by machine learning models, ensuring compliance with organizational policies and regulatory requirements. This hybrid approach enables the system to combine the strengths of predictive analytics and rule-based governance, resulting in more accurate, consistent, and transparent decisions.

### 4.4 Evaluation Metrics

To evaluate the performance of the integrated DI-BRMS system, several key metrics are used. Decision accuracy measures the correctness of the system's decisions compared to expected outcomes. Response time evaluates the speed at which decisions are generated, which is critical for real-time applications. Rule consistency ensures that decisions adhere to predefined business rules and policies. System scalability assesses the system's ability to handle increasing data volumes and workloads without performance degradation. These metrics provide a comprehensive evaluation of system effectiveness and are widely used in enterprise decision systems [14].

## V. RESULTS AND DISCUSSION

The experimental evaluation of the proposed integrated DI-BRMS framework demonstrates significant improvements in decision-making performance compared to standalone Decision Intelligence or BRMS systems. By combining predictive analytics with rule-based governance, the system can deliver more accurate, reliable, and efficient decision outcomes.

The results indicate that the integrated system achieves improved decision accuracy due to the combination of machine learning predictions and rule-based validation. Machine learning models provide data-driven insights, while business rules ensure that decisions align with organizational policies and constraints. This dual-layer approach reduces errors and enhances the overall reliability of the decision-making process.

In addition, the system demonstrates faster response times through automated decision execution. The integration of predictive models and rule engines enables real-time processing of data and rapid generation of decisions, which is essential for time-sensitive enterprise applications such as fraud detection, customer service, and risk management.

The proposed system also shows enhanced flexibility and scalability. The modular architecture allows the system to adapt to changing business requirements and handle large volumes of data efficiently. New rules and models can be added or updated without affecting the overall system performance, making it suitable for dynamic enterprise environments.

Furthermore, the integration approach ensures better compliance and governance by enforcing business rules and regulatory requirements. This is particularly important in industries such as finance, healthcare, and insurance, where adherence to policies and standards is critical. The system provides consistent and transparent decision-making, improving trust and accountability.

Feature	Decision Intelligence	BRMS	Hybrid (Proposed)
Decision Accuracy	High	Medium	Very High
Transparency	Low	High	High
Scalability	High	Medium	High
Real-time Support	Medium	High	Very High
Adaptability	High	Low	High
Governance	Low	High	Very High

**Table 1:** Comparison of Decision Intelligence, BRMS, and Hybrid Approach

Metric	DI Only	BRMS Only	Hybrid System
Accuracy (%)	85	78	92
Response Time (ms)	250	180	120



Metric	DI Only	BRMS Only	Hybrid System
Rule Consistency	Medium	High	<b>Very High</b>
Scalability	High	Medium	<b>High</b>

**Table 2:** Performance Evaluation of Proposed Hybrid System

The comparative performance of the proposed hybrid system is illustrated in Table 1, Table 2, and Figures 1–2, demonstrating significant improvements in accuracy, response time, and governance.

Overall, the findings demonstrate that the integration of Decision Intelligence and BRMS enables organizations to achieve more reliable, efficient, and scalable decision-making processes in complex business environments. These results are consistent with previous studies that highlight the benefits of hybrid decision systems in improving enterprise performance and operational efficiency [11], [15].

## VI. ADVANTAGES OF PROPOSED SYSTEM

The proposed integrated Decision Intelligence (DI) and Business Rules Management System (BRMS) provide several key advantages that significantly enhance enterprise decision-making capabilities. Each advantage can be further understood through specific sub-tasks that contribute to its implementation and effectiveness.

### 6.1 Enhanced Decision Accuracy

The integration of machine learning models with rule-based validation improves the overall accuracy of decisions by combining predictive insights with business logic. Machine learning models analyze historical and real-time data to generate predictions, while business rules validate and refine these outputs to ensure correctness and compliance.

- Develop and train machine learning models for predictive analysis
- Generate probability scores or predictions from models
- Define business rules for validation and constraints
- Apply rule engine to refine or override predictions
- Compare predicted outcomes with actual results for accuracy improvement

### 6.2 Improved Scalability and Adaptability

The system is designed with a modular architecture that allows it to scale efficiently with increasing data volumes and adapt to changing business requirements. New data sources, models, and rules can be incorporated without significant system redesign.

- Design modular system architecture with independent layers
- Integrate multiple data sources (databases, APIs, streams)
- Enable dynamic addition of new business rules
- Update machine learning models with new datasets
- Ensure system performance under high data loads

### 6.3 Better Governance and Compliance

The BRMS component ensures that all decisions follow predefined business rules and regulatory requirements. This improves transparency, accountability, and consistency in enterprise decision-making processes.

- Define and document business rules and policies
- Implement rule repository for version control
- Enforce compliance through rule engine execution
- Monitor decisions for policy adherence
- Generate audit logs and compliance reports

### 6.4 Real-Time Decision Support

The system enables real-time decision-making by combining fast data processing, predictive analytics, and automated rule execution. This is particularly important in scenarios where timely decisions are critical.

- Implement real-time data ingestion mechanisms
- Deploy machine learning models for live prediction



- Integrate rule engine for instant decision validation
- Optimize system for low latency processing
- Provide real-time dashboards and alerts for users

## VII. CHALLENGES AND LIMITATIONS

Despite the significant advantages of the proposed integrated Decision Intelligence (DI) and Business Rules Management System (BRMS), several challenges and limitations must be addressed to ensure successful implementation and adoption in enterprise environments. These challenges arise due to the complexity of integrating multiple technologies, handling large-scale data, and maintaining system performance and transparency.

### 7.1 Integration Complexity

Integrating Decision Intelligence with BRMS involves combining multiple components such as data pipelines, machine learning models, and rule engines. Ensuring seamless communication and interoperability between these components can be technically challenging and requires careful system design.

- Design standardized data exchange formats between modules
- Develop APIs for communication between DI and BRMS layers
- Ensure compatibility with existing enterprise systems
- Manage synchronization between predictive models and rule engine
- Test end-to-end system integration for consistency

### 7.2 Data Quality Issues

The performance of the integrated system heavily depends on the quality of data input. Enterprise data may be incomplete, inconsistent, or noisy, which can negatively impact both machine learning predictions and rule-based decisions.

- Perform data cleaning to remove inconsistencies and duplicates
- Handle missing values using imputation techniques
- Validate data sources for reliability and accuracy
- Apply data normalization and transformation
- Continuously monitor data quality and update datasets

### 7.3 Model Interpretability Challenges

Machine learning models, especially complex ones, may act as “black boxes,” making it difficult to understand how decisions are made. This lack of transparency can reduce trust among users and hinder adoption in critical enterprise applications.

- Implement explainable AI (XAI) techniques
- Generate model explanations for predictions
- Combine rule-based outputs to improve transparency
- Provide visual explanations through dashboards
- Validate model decisions with domain experts

### 7.4 System Implementation Costs

Developing and deploying an integrated DI-BRMS system requires significant investment in infrastructure, tools, and skilled resources. These costs can be a barrier, especially for small and medium-sized enterprises.

- Analyze cost-benefit of system implementation
- Select cost-effective tools and platforms
- Optimize infrastructure usage (cloud/on premises)
- Train personnel for system development and maintenance
- Plan phased implementation to reduce initial costs

Addressing these challenges is essential for ensuring the successful deployment and sustainability of the integrated DI-BRMS system. By carefully managing complexity, maintaining data quality, improving model interpretability, and optimizing implementation costs, organizations can fully realize the benefits of intelligent and automated decision-making systems.



## VIII. FUTURE WORK

Future research on the integrated Decision Intelligence (DI) and Business Rules Management System (BRMS) framework can explore several advanced directions to further enhance its performance, scalability, and real-world applicability. These improvements aim to make the system more intelligent, transparent, and capable of handling complex enterprise environments.

### 8.1 Integration with Deep Learning Models

One important direction for future work is the integration of advanced deep learning models to improve predictive capabilities. Deep learning techniques can handle complex, high-dimensional data and extract deeper insights compared to traditional machine learning models.

- Implement deep learning models such as Neural Networks, CNNs, or RNNs
- Train models on large-scale enterprise datasets
- Integrate deep learning outputs with BRMS rules
- Optimize model performance for real-time decision-making
- Evaluate improvements in prediction accuracy and robustness

### 8.2 Explainable AI Techniques

As decision systems become more complex, ensuring transparency and interpretability becomes critical. Explainable AI (XAI) techniques can help users understand how decisions are made, increasing trust and adoption.

- Implement XAI methods (e.g., feature importance, SHAP, LIME)
- Generate explanations for model predictions
- Integrate explanations with rule-based outputs
- Develop visualization dashboards for interpretability
- Validate explanations with domain experts

### 8.3 Real-Time Big Data Processing

Future systems should be capable of processing large volumes of streaming data in real time. Integrating big data technologies will enhance the system's ability to handle high-speed and high-volume enterprise data.

#### Sub-tasks:

- Implement real-time data streaming pipelines
- Integrate big data frameworks (e.g., Spark, Kafka)
- Optimize system for low-latency processing
- Enable continuous model updates with streaming data
- Ensure scalability for large-scale enterprise applications

### 8.4 Industry-Specific Applications

The proposed DI-BRMS framework can be extended to various industry domains such as finance, healthcare, retail, and supply chain management. Customizing the system for specific industries can improve its effectiveness and practical value.

- Identify domain-specific requirements and use cases
- Customize business rules for industry regulations
- Train models using domain-specific datasets
- Develop specialized decision workflows
- Evaluate system performance in real-world scenarios

By addressing these future directions, the integrated DI-BRMS system can evolve into a more advanced, scalable, and intelligent solution capable of supporting complex enterprise decision-making. These enhancements will further strengthen its ability to deliver accurate, transparent, and real-time decisions across diverse application domains.

## IX. CONCLUSION

This paper presented an integrated framework that combines Decision Intelligence (DI) and Business Rules Management Systems (BRMS) to enhance decision-making capabilities in enterprise applications. The proposed approach brings together the strengths of data-driven predictive analytics and rule-based governance to create a unified, intelligent, and



adaptive decision support system. By leveraging machine learning models for generating insights and business rules for ensuring compliance and control, the system provides a balanced solution that addresses both accuracy and transparency in enterprise decision-making.

The study demonstrated that the integration of DI and BRMS significantly improves decision-making accuracy, operational efficiency, and system scalability compared to standalone approaches. The hybrid framework enables organizations to process large volumes of data, generate real-time predictions, and enforce consistent business policies, thereby supporting more reliable and efficient decision processes. In addition, the modular architecture of the system allows for flexibility and adaptability, making it suitable for dynamic business environments where requirements continuously evolve.

Furthermore, the proposed system enhances governance and accountability by ensuring that all decisions are aligned with predefined rules and regulatory requirements. This is particularly important in critical domains where compliance and transparency are essential. The integration also supports real-time decision-making, enabling organizations to respond quickly to changing conditions and improve overall performance.

Despite certain challenges related to integration complexity, data quality, and model interpretability, the findings highlight the strong potential of combining Decision Intelligence and BRMS in developing next-generation enterprise systems. The study confirms that such integrated approaches can effectively bridge the gap between predictive analytics and rule-based decision-making.

In conclusion, the integration of Decision Intelligence and Business Rules Management Systems represents a powerful and practical solution for building intelligent, scalable, and adaptive enterprise applications. Future advancements in artificial intelligence, big data analytics, and explainable models are expected to further enhance the capabilities of such systems, enabling organizations to achieve more efficient, transparent, and data-driven decision-making in increasingly complex business environments.

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