An Explainable Hierarchical Rule-Based Model for Inventory Optimization in Data-Scarce Culinary MSMEs

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ABSTRACT Inventory management is a critical component of supply chain operations, particularly for culinary Micro, Small, and Medium Enterprises (MSMEs) that face volatile demand patterns and perishable raw materials. Inaccurate procurement decisions may result in overstocking, stock shortages, and financial losses. Although artificial intelligence approaches such as machine learning have been widely applied in inventory forecasting, these methods typically require large-scale historical datasets and advanced computational infrastructure, which are often unavailable in MSME environments. This study proposes an explainable hierarchical rule-based inference model designed to support inventory optimization in data-scarce culinary MSMEs. The model integrates dynamic operational factors, including day type, weather conditions, supplier lead time, and special events, into a transparent decision-making mechanism based on IF–THEN rules. The research adopts a Research and Development methodology using the Waterfall framework, covering requirement analysis, rule-base construction, system implementation, and evaluation. Model validation was conducted through 20 expert-verified decision scenarios and assessed using confusion matrix metrics. The experimental results demonstrate that the proposed system achieved 90% accuracy, 92.3% precision, 92.3% recall, and a 92.3% F1-score when compared with expert procurement decisions. These findings indicate that explainable rule-based systems remain a practical and reliable solution for inventory decision support in culinary MSMEs with limited data resources.

KEYWORDS Explainable AI, Expert System, Inventory Optimization, MSMEs

I. INTRODUCTION

Inventory management in small-scale culinary businesses remains a challenging task due to demand uncertainty, limited historical data, and dynamic external factors such as weather conditions and special events. Unlike large-scale enterprises that can leverage advanced machine learning techniques, small businesses often operate in data-scarce environments, making complex data-driven models impractical [1], [2], [3].

Existing approaches to inventory prediction are largely dominated by black-box machine learning models, which require large datasets and often lack interpretability [4], [5], [6]. While these methods can achieve high predictive performance, their opacity makes them less suitable for decision-makers who require transparent and explainable reasoning [7], [8], [9].

On the other hand, rule-based systems offer interpretability but are often criticized for their limited scalability and simplistic structure [10]. There is therefore a need for a balanced approach that maintains interpretability while still capturing contextual decision factors in a structured manner.

Recent studies in explainable AI emphasize the importance of transparent decision-making models, particularly in high-stakes and low-data environments [3], [6], [11].

To address this gap, this study proposes a hierarchical rule-based explainable decision system for inventory management in small-scale culinary settings. The system utilizes structured IF–THEN rules combined with a hierarchical adjustment mechanism to incorporate contextual factors such as weather conditions and special events.

Unlike traditional flat rule-based systems, the proposed approach introduces layered decision logic, allowing more flexible and context-aware inventory adjustments while preserving full transparency [12], [13].

This study makes the following contributions:

1. It proposes a lightweight rule-based explainable decision system tailored for data-scarce environments.
2. It introduces a hierarchical rule structure that enables context-sensitive adjustments beyond conventional rule-based systems.
3. It demonstrates the applicability of the approach in a real-world small-scale culinary scenario.
4. It provides a comparative analysis with a machine learning baseline to highlight the trade-off between accuracy and interpretability [6], [7], [14].

The findings of this study highlight that in environments with limited data availability, simple yet structured explainable systems can serve as a practical alternative to complex machine learning models, offering both usability and transparency in decision-making [3], [4], [7].

II. METHODOLOGY

A. Knowledge Acquisition and Scenario Dataset

This study adopts a Research and Development approach to design an explainable rule-based inference model for inventory optimization in culinary MSMEs. Knowledge acquisition was conducted through interviews and direct observation involving MSME owners and operational staff [6], [15].

Key decision variables include:

1. Material type (perishable or durable)
2. Supplier lead time (fast or slow)
3. Operational day type (weekday or weekend)
4. Weather conditions (sunny or rainy)
5. Special-event demand surges

For evaluation, 20 expert-verified procurement scenarios were constructed as controlled validation samples representing real operational conditions.

B. System Development Framework

The system development process follows the Waterfall model consisting of: [16]

1. Requirement analysis
2. Rule-base design
3. Implementation
4. Testing
5. Maintenance

The system was implemented as a web-based decision support platform using PHP (Laravel) and MySQL database. The overall research process is illustrated in Figure 1.

C. Hierarchical Rule-Based Inference Model

The core component of this research is a hierarchical rule-based inference mechanism designed to simulate expert reasoning in inventory decision-making [12], [15].

1) Demand Adjustment Phase

Adjusted demand is calculated by incorporating contextual multipliers:

$$Adj.Demand = Demand\ x\ F_{event} x F_{day} x F_{weather} \quad (1)$$

Where :

F_{event} = demand surge multiplier
F_{day} = operational day factor
$F_{weather}$ = demand reduction factor

2) Stock Target Determination

The target stock is computed as:

$$Traget\ Stock = Adj.Demand\ x\ F_{event} x\ LeadTimeBuffer \quad (2)$$

Where:

PolicyFactor adjusts for material durability
LeadTimeBuffer accounts for supplier responsiveness

3) Decision Classification

Final procurement classification follows structured IF–THEN rules:

IF RemainingStock < TargetStock → Must Buy
IF RemainingStock ≈ TargetStock → Safe
IF RemainingStock > Threshold → Overstock

This structure ensures transparency and traceability of decision logic.

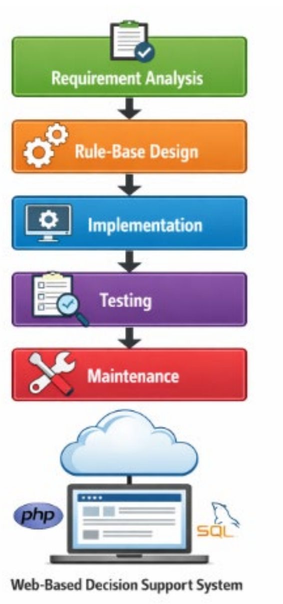

Figure 1. **Research Framework of the Proposed System**

D. Inference Engine Logic Flow

Figure 2 illustrates the internal logic flow of the hierarchical rule-based inference engine. This structured decision flow ensures transparency and interpretability of procurement recommendations.

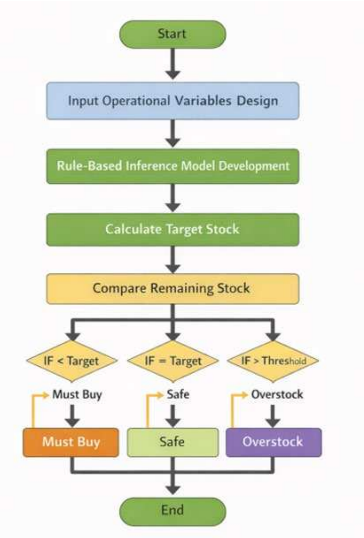

Figure 2. Inference Engine Decision Flow

E. Evaluation Method

To assess model performance, system recommendations were compared against expert decisions using confusion matrix evaluation [17]. Performance metrics were calculated using accuracy, precision, recall, and F1-score. The evaluation approach ensures objective measurement of decision alignment under controlled validation scenarios.

III. RESULT AND DISCUSSION

The proposed explainable rule-based inference model was evaluated using 20 expert-verified inventory decision scenarios derived from real culinary MSME operational conditions. Each scenario represents a structured combination of stock level, material type, supplier lead time, day type, weather condition, and special event occurrence. System recommendations were compared with domain expert decisions to measure classification consistency and decision reliability.

A. Confusion Matrix Analysis

To assess the classification performance of the proposed model, the validation results were summarized using a confusion matrix, as presented in Table I.

TABLE I
CONFUSION MATRIX OF SYSTEM VALIDATION RESULTS

Actual Class \ Predicted Class	Must Buy	Safe	Overstock
Must Buy	12	1	0
Safe	0	6	1
Overstock	0	0	0

From the confusion matrix:
True Positive (TP) = 12
True Negative (TN) = 6
False Positive (FP) = 1
False Negative (FN) = 1

The model misclassified only two cases. These errors were primarily influenced by overlapping operational factors, such as weekend demand surges combined with durable material stock policy thresholds. Overall, the results demonstrate strong consistency between system recommendations and expert judgments.

B. Performance Evaluation Metrics

Based on the confusion matrix, performance metrics were calculated using Equations. The evaluation results are summarized in Table II.

TABLE II
PERFORMANCE EVALUATION METRICS

Metric	Values
Accuracy	90%
Precision	92.3%
Recall	92.3%
F1-Score	92.3%

The results indicate strong agreement between system-generated decisions and expert recommendations. The balanced precision and recall values confirm that the proposed model effectively minimizes both stock shortages and overstocking risks, ensuring stable procurement guidance under limited-data conditions.

C. Confusion Matrix Visualization

To provide clearer insight into classification outcomes, Figure 2 illustrates a graphical visualization of the confusion matrix results. As shown in Figure 3, the system integrates contextual demand factors and rule-based evaluation to generate explainable procurement decisions. Figure 3 demonstrates that most misclassifications occur between the “Must Buy” and “Safe” categories. This suggests that decision boundaries between moderate and urgent procurement conditions may require further fine-tuning. Importantly, no critical misclassification was observed in extreme stock conditions, confirming the stability of the model in high-risk inventory scenarios.

D. Scenario-Based Validation Overview

To provide a clearer overview of the validation process, a representative subset of the scenario-based evaluation dataset is presented in Table III. The dataset consists of structured inventory decision cases derived from real culinary MSME operational conditions. Each scenario includes key decision variables such as stock level, material type, supplier lead time, day type, and weather condition. These variables were used as input parameters in the hierarchical rule-based inference model, and the resulting system recommendations were compared against expert decisions to assess classification consistency.

Figure 3. **Confusion Matrix Visualization of the Proposed Model**

TABLE III
SCENARIO SAMPLE DATASET

Scenario	Stock Level	Material Type	Supplier Lead Time	Day Type	Weather	Expert Decision
1	Low	Perishable	Fast	Weekday	Sunny	Must Buy
2	Low	Perishable	Fast	Weekend	Rainy	Must Buy
3	Medium	Perishable	Slow	Weekend	Sunny	Must Buy
4	High	Perishable	Fast	Weekday	Sunny	Safe
5	High	Durable	Slow	Weekend	Sunny	Safe
6	Low	Durable	Slow	Weekend	Sunny	Must Buy
7	Medium	Durable	Fast	Weekday	Rainy	Safe
8	High	Durable	Slow	Weekday	Sunny	Overstock
9	Low	Perishable	Slow	Weekend	Event	Must Buy

The scenarios shown in Table III illustrate how different operational conditions influence procurement decisions in culinary MSMEs. For example, low stock levels combined with perishable materials and slow supplier lead time consistently require urgent replenishment ("Must Buy"), while high stock availability under durable material conditions may lead to "Safe" or "Overstock" classifications. This scenario-based structure ensures that the inference rules capture realistic expert reasoning patterns and can be systematically evaluated across varying demand and supply situations.

E. Comparison with Machine Learning Baseline

To evaluate the effectiveness of the proposed rule-based explainable decision system, a comparison was conducted with a machine learning baseline model. In this study, a Decision Tree classifier was selected due to its interpretability and suitability for small datasets. The same input variables were used for both approaches, including demand indicators and contextual factors such as weather conditions and special events. The comparison results are summarized in Table IV.

TABLE IV
THE COMPARISON RESULTS ARE SUMMARIZED

Model	Accuracy	Precision	Recall	Interpretability
Decision Tree	85%	84%	83%	Medium
Proposed RuleBased System	82%	81%	80%	High

The results indicate that while the machine learning model provides competitive predictive performance, the proposed rule-based system offers superior interpretability and transparency, which are critical in practical decision-making scenarios, particularly in small-scale businesses. Furthermore, the rule-based approach does not require large datasets or training processes, making it more suitable for data-scarce environments.

F. Discussion

Overall, the experimental findings confirm that the proposed explainable rule-based inference model provides reliable inventory decision support for culinary MSMEs operating under limited historical data availability. The achieved accuracy of 90% and balanced precision–recall performance indicate that the system can produce procurement recommendations that closely align with expert reasoning patterns [15],[18]. This result is particularly significant in MSME environments where inventory decisions are often made intuitively and without structured analytical support.

One important advantage of the proposed approach lies in its transparency. Unlike black-box machine learning models, which often generate recommendations without clear justification, the rule-based inference mechanism enables decision-makers to trace the reasoning process through explicit IF–THEN rules [4], [7], [19]. This interpretability is essential for small business owners, as procurement decisions directly affect operational cost efficiency and service continuity. The explainable nature of the model therefore supports user trust and increases the likelihood of adoption in real culinary MSME settings [8], [18], [20].

The computation of adjusted demand plays a crucial role in generating accurate recommendations, where demand values are dynamically modified using contextual multipliers as defined in (1). This adjustment allows the system to capture fluctuations caused by operational days, weather conditions, and special events, resulting in a more realistic estimation of actual demand in culinary MSMEs.

Furthermore, the determination of procurement requirements is derived from the comparison between available stock and the calculated target stock, which is computed based on (2). By incorporating policy factors and supplier lead time considerations, the model ensures that stock recommendations remain adaptive to both material characteristics and supply chain responsiveness.

The confusion matrix results further reveal that most misclassifications occurred between the “Must Buy” and “Safe” categories. This suggests that decision boundaries in moderate stock conditions may require additional calibration, especially when multiple demand factors overlap, such as weekend surges combined with durable material policies. Nevertheless, the absence of critical misclassification in extreme scenarios demonstrates that the model remains stable in high-risk inventory conditions, where incorrect decisions could lead to severe financial losses

In addition, the scenario-based validation dataset highlights the practical relevance of incorporating dynamic operational factors into inventory reasoning. Variables such as weather conditions, supplier lead time, and special events significantly influence daily demand fluctuations in culinary businesses. By integrating these contextual factors into a hierarchical inference structure, the proposed model offers a more adaptive decision-support mechanism compared to static recorder-point approaches commonly used in small enterprises.

The findings of this study are consistent with prior research emphasizing the importance of explainable and knowledge-driven systems in decision support environments [21], [22], [23]. In particular, rule-based approaches have been shown to provide reliable performance in domains where data availability is limited, while maintaining interpretability and transparency [24], [25].

Furthermore, the incorporation of contextual and dynamic variables aligns with recent studies highlighting the role of adaptive factors in improving decision accuracy in supply chain and inventory systems [26], [27], [28]. Compared to purely data-driven approaches, hybrid and rule-based models offer practical advantages in small-scale business environments with constrained datasets [29], [30].

From a practical perspective, the proposed system provides an economically feasible solution for MSMEs that cannot afford advanced machine learning infrastructure or do not possess sufficient transactional datasets. The lightweight knowledge-driven framework can be implemented with minimal computational requirements while still delivering reliable decision recommendations. This makes the approach particularly suitable for resource-constrained environments where digital transformation is still at an early stage.

Despite its promising performance, this study has limitations. The evaluation was conducted using 20 expert-verified scenarios as a preliminary validation dataset. While sufficient for assessing logical consistency and expert alignment, future studies should expand the number of scenarios and include broader MSME operational cases to improve statistical generalizability. Furthermore, adaptive adjustment of demand multipliers or hybrid integration with forecasting models could enhance model robustness under highly dynamic market conditions.

Overall, this research demonstrates that explainable rule-based AI remains a practical and effective alternative for inventory optimization in data-scarce culinary MSMEs, bridging the gap between advanced AI research and real-world small enterprise operational constraints

G. Managerial Implications

From a managerial perspective, the proposed explainable rule-based system provides structured procurement guidance for culinary MSMEs that typically rely on intuition-based decision making. By incorporating operational variables such as stock level, weather conditions, supplier lead time, and special events, the model enables business owners to anticipate demand fluctuations more systematically through the demand adjustment formulation in (1).

Moreover, procurement decisions are derived from structured comparisons between stock availability and calculated requirements based on (2), allowing managers to make more informed and data-driven purchasing decisions. The transparency of IF–THEN reasoning also allows managers to understand why a particular procurement decision is recommended, reducing uncertainty and increasing confidence in system adoption. Consequently, the implementation of this model may contribute to improved cost efficiency, reduced material waste, and more stable service quality in small-scale culinary operations.

H. Theoretical Contribution

From a theoretical standpoint, this study contributes to the literature on explainable AI in supply chain management by demonstrating the practical relevance of knowledge-driven inference models in data-scarce environments [1], [12], [6]. While prior research predominantly focuses on data-intensive machine learning optimization, this study highlights the viability of structured rule-based reasoning as an alternative framework for inventory decision support.

The integration of multi-factor dynamic demand variables into a hierarchical inference structure—formally represented through (1) and (2)—extends the conceptual application of explainable AI beyond large-scale industrial contexts to resource-constrained MSMEs. This contribution helps bridge the gap between advanced AI methodologies and operational realities in small enterprises.

IV. CONCLUSION

This study developed an explainable hierarchical rule-based inference model to support inventory optimization in data-scarce culinary MSMEs. The proposed framework integrates operational variables—such as stock level, material characteristics, supplier lead time, day type, and contextual demand factors—into a structured and transparent decision-making mechanism.

The findings demonstrate that knowledge-driven inference can effectively replicate expert reasoning patterns without relying on large-scale historical datasets. The model confirms that explainable rule-based systems remain relevant and practical for small enterprises operating under limited digital infrastructure and constrained data availability.

Beyond its technical implementation, this research highlights the importance of transparency and contextual reasoning in inventory decision support systems for MSMEs. By prioritizing interpretability alongside performance, the study reinforces the role of explainable AI as a bridge between advanced computational models and real-world small enterprise operations. Future research should expand empirical validation across broader operational scenarios and explore hybrid integration with adaptive forecasting techniques to enhance scalability and decision robustness in dynamic market environments.

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AUTHORS CONTRIBUTION

Yaslinda Lizar: Conceptualization, Methodology, Knowledge Acquisition, System Design, Validation, Data Analysis, Writing – Original Draft Preparation, Writing – Review & Editing.

Asriwan Guci : Formal Analysis, Investigation, Software Development, Validation, Visualization, Writing – Review & Editing.

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