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Forward Chaining Expert System for Optimizing Marketing Strategies in Social Commerce Platforms

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Abstract
The complexity of digital performance indicators in social commerce environments poses significant challenges for small and medium enterprises (SMEs) in formulating coherent and actionable marketing strategies. This study develops and evaluates a forward chaining based expert system to support structured, data driven, and interpretable marketing decision-making. A design science research methodology was employed, encompassing problem identification, artifact development, and evaluation. Knowledge was elicited through literature synthesis, expert consultation, and empirical observation, and subsequently formalized into IF–THEN production rules within a structured knowledge base. The system applies a forward chaining inference mechanism to process key indicators, including followers, engagement rate, promotion frequency, and conversion rate, in order to generate prioritized strategic recommendations. Evaluation was conducted using scenario-based testing and expert validation to assess accuracy, consistency, and contextual appropriateness. The results demonstrate complete alignment between system outputs and expert judgment across all evaluation scenarios, indicating high reliability and logical consistency of the rule-based reasoning process. The system also produces context-sensitive and interpretable recommendations aligned with varying levels of business performance. This study contributes by advancing rule-based decision support systems in social commerce and providing an explainable and practically applicable tool to enhance marketing decision quality among SMEs.

Keywords: decision support system; expert system; forward chaining; marketing strategy; social commerce

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INTRODUCTION

The expansion of digital ecosystems has redefined contemporary marketing practices through the emergence of social commerce, wherein content creation, user interaction, and transactional processes converge within unified platform environments. Platforms such as TikTok Shop facilitate direct engagement between small and medium enterprises (SMEs) and consumers, while simultaneously generating diverse digital performance indicators, including follower growth, engagement rate, promotion frequency, and conversion rate (Almtiri et al., 2022; Olan et al., 2024; Dwivedi et al., 2023).

The increasing availability of such indicators introduces a critical challenge related to their interpretation and strategic utilization. In many cases, SMEs continue to rely on intuition or fragmented analytical approaches, resulting in inconsistent decision-making and limited optimization of marketing outcomes (Huang & Rust, 2021; Lee et al., 2022; Volkmar, 2022). The central issue, therefore, lies in the absence of structured mechanisms capable of transforming heterogeneous performance data into coherent and actionable marketing strategies (Alghamdi & Al-Baity, 2022; Punia & Shankar, 2022).

Decision Support Systems (DSS) play an important role in improving decision-making quality through the use of data and analytical models; however, their effectiveness is not solely determined by accuracy, but also by transparency and interpretability of the outputs. The concept of *explainable artificial intelligence* (XAI) has become essential, as it enhances clarity and user trust in systems, especially when complex or *black box* models are employed (Gunning & Aha, 2019; Li et al., 2022; Tjoa & Guan, 2020). User trust is strongly influenced by the system's ability to provide clear and understandable explanations, particularly in organizational contexts and among small and medium enterprises (SMEs), where technical expertise may be limited (Kshetri et al., 2023; Kumari et al., 2025; Rai, 2020; Younis et al., 2022).

At the same time, there is a trade-off between model complexity and transparency, where higher predictive performance often comes at the cost of reduced (Rajagopal et al., 2022; Rudin, 2019). Various explainability techniques, such as feature importance and local explanations, have been proposed to improve system accountability and user understanding (Akter et al., 2022; Allen et al., 2023; Kruschel et al., 2026; Mohamed et al., 2025). Overall, the successful implementation of modern DSS depends on achieving a balance between analytical performance, transparency, and the system's ability to clearly explain its decision-making processes.

Existing studies highlight critical shortcomings in current approaches to marketing decision support. Machine learning based methods predominantly prioritize predictive performance while providing limited interpretability, which restricts their practical adoption in SME context (Du et al., 2022; Pumplun et al., 2023; Rudin, 2019). Conversely, rule-based expert systems provide transparency but are often characterized by static rule structures and insufficient integration of multi-dimensional performance indicators (Islam & Governatori, 2018; Keshireddy, 2024; Li et al., 2022; Papadopoulos et al., 2022; Zatnika & Rukhviyanti, 2024). Furthermore, research in social commerce has largely focused on descriptive analytics or platform-specific optimization, with limited attention to structured mechanisms that transform diverse digital performance metrics into prioritized and actionable strategies (Attar et al., 2022; Zhang & Benyoucef, 2016; Zhao et al., 2023). These limitations indicate the absence of an approach that simultaneously integrates data-driven capability, interpretability, and contextual relevance within a unified decision-support framework.

The identified limitations indicate the absence of a decision-support mechanism capable of systematically integrating multiple digital performance indicators into interpretable and prioritized marketing strategies within social commerce environments. Existing approaches remain fragmented, either emphasizing predictive capability with limited transparency or prioritizing interpretability without sufficient contextual integration (Dong et al., 2022; Rudin, 2019). This study proposes a forward chaining based expert system as a methodological alternative that enables sequential, data-driven reasoning while preserving transparency and logical consistency (Kostopoulos et al., 2024; Navin & Krishnan, 2024). By initiating inference from observable performance indicators and activating relevant rules, this approach ensures that recommendations are interpretable, traceable, and aligned with practical decision-making contexts, thereby enhancing usability and decision quality in SME environments.

This study develop and evaluate a forward chaining based expert system for optimizing marketing strategies in social commerce platforms through the structured transformation of multiple digital performance indicators into actionable recommendations. The novelty is reflected in the integration of heterogeneous performance metrics within a unified rule-based framework, the implementation of forward chaining inference to enable data-driven yet interpretable reasoning, and the incorporation of priority levels to enhance decision relevance and practical applicability. The study contributes theoretically by extending the conceptual development of decision support systems and expert systems through structured rule-based integration, and practically by providing an interpretable tool that supports SMEs in improving the consistency, accuracy, and effectiveness of marketing decision-making within dynamic social commerce environments.

METHOD

This study employs a Design Science Research (DSR) methodology to develop and rigorously evaluate a decision-support artifact in the form of a forward chaining based expert system for marketing strategy optimization in social commerce environments. The DSR approach is widely recognized in contemporary information systems research for its ability to systematically develop and evaluate artifacts that address complex decision-making problems (Pumplun et al., 2023; Sabharwal et al., 2025). The research process encompasses problem identification, definition of objectives, artifact design and development, demonstration, and evaluation, ensuring both theoretical grounding and practical relevance.

Knowledge acquisition is conducted using a triangulated approach that integrates a structured literature review, empirical observations of SME practices within social commerce platforms, and expert elicitation through semi-structured interviews. The study involves five informants, consisting of digital marketing practitioners, SME owners, and an academic expert in information systems, selected based on domain expertise and practical experience. Interview data are transcribed and analyzed using qualitative content analysis, including open coding to identify key concepts, axial coding to establish relationships between conditions and corresponding strategic actions, and selective coding to construct structured IF–THEN decision rules. To enhance methodological rigor, triangulation across data sources and consistency checking are applied to ensure the validity and reliability of the extracted knowledge.

The proposed system is designed as a rule-based expert system employing forward chaining as its inference mechanism. Knowledge is represented in the form of IF–THEN production rules derived from both expert knowledge and empirical patterns observed in real business contexts. The knowledge base consists of 11 rules representing combinations of four key performance indicators: followers, engagement rate, promotion frequency, and conversion rate. Each variable is operationalized using standardized quantitative formulations. Engagement rate is calculated as the ratio of total interactions to total followers multiplied by 100, while conversion rate is defined as the ratio of completed transactions to total visitors. Promotion frequency is measured based on the number of posts per week, and follower count represents audience size. Each variable is discretized into three categorical levels—low, medium, and high based on empirical distribution and expert-defined thresholds to ensure consistency and interpretability.

The system operates by processing user inputs as initial facts stored in working memory. The forward chaining inference mechanism evaluates these facts sequentially against the rule base, activating rules whose conditions are satisfied. Each activated rule produces a corresponding marketing strategy recommendation along with a priority level (high, medium, or low), reflecting the urgency and importance of the recommended action. The reasoning process proceeds iteratively until all relevant rules have been evaluated, ensuring that outputs are logically consistent, traceable, and aligned with input conditions. A fallback mechanism is incorporated to maintain system robustness in cases where no exact rule match is identified.

System evaluation is conducted using 50 test scenarios derived from real SME data and simulated conditions to ensure coverage of diverse performance configurations. The evaluation framework employs accuracy, precision, and conformity rate as performance metrics by comparing system-generated recommendations with expert judgments as the ground truth. Accuracy is defined as the proportion of correct recommendations relative to total test cases, while precision reflects the consistency of rule activation in producing valid outputs. Conformity rate measures the degree of alignment between system outputs and expert expectations in terms of contextual relevance. In addition, statistical validation using paired comparison is applied to assess the significance of performance differences between the proposed system and baseline approaches, including manual decision-making and non-structured recommendation methods. The evaluation results provide evidence of the system’s reliability, consistency, and effectiveness in generating interpretable and actionable marketing strategies within social commerce environments.

RESULTS AND DISCUSSION

Results

The results of this study demonstrate the effectiveness of the proposed forward chaining based expert system in generating structured, interpretable, and context-sensitive marketing strategy recommendations. The findings are presented in four main components: system implementation, knowledge representation, system performance evaluation, and analytical insights. Figure 1 presents the user interface of the developed expert system for digital marketing strategy recommendations. The interface is structured into two main sections: an input panel for entering key performance indicators such as followers and engagement rate and an output panel for displaying system-generated recommendations. The system processes user inputs using a forward chaining inference mechanism, enabling the transformation of performance data into actionable and prioritized marketing strategies. The layout emphasizes clarity and usability, allowing users to easily interact with the system and understand how input conditions lead to specific recommendations.

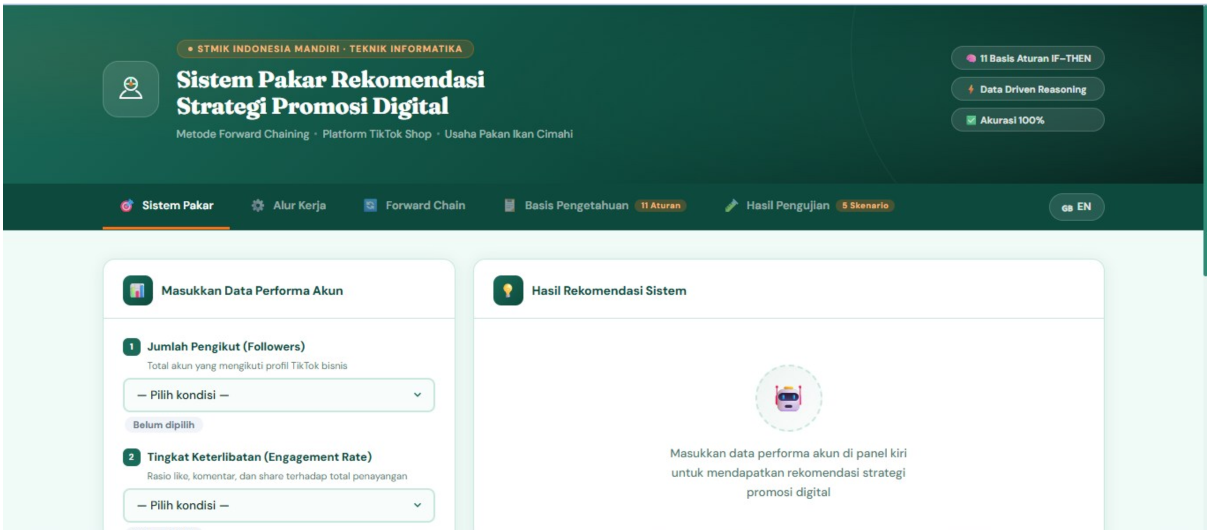

Figure 1. User interface of the proposed expert system

The system knowledge is formalized into 11 IF–THEN production rules that represent combinations of performance indicators and corresponding strategic actions. These rules encode expert knowledge into a structured format that enables systematic reasoning. Table 1 presents the structure of the knowledge base, which encodes expert reasoning into 11 IF–THEN production rules. Each rule represents a unique combination of performance indicators and is associated with a specific strategic recommendation and priority level. The table shows that the system is designed to capture different stages of business performance, ranging from low to high conditions. In low-performance scenarios (e.g., R1–R3), the system prioritizes fundamental improvements such as content development and engagement enhancement. In contrast, high-performance conditions (R9–R11) shift toward optimization and sustainability strategies. The inclusion of priority levels further strengthens the decision-support capability by indicating the urgency of each recommendation.

Table 1. Structure of if–then rules in the expert system

Rule	Followers	Engagement	Frequency	Conversion	Recommendation Focus	Priority
R1	Low	Low	Low	Low	Content & promotion improvement	High
R2	Low	Medium	Low	Low	Engagement optimization	High
R3	Medium	Low	Medium	Low	Content refinement	High
R4–R8	Mixed	Mixed	Mixed	Mixed	Tactical adjustment	Medium
R9	High	Medium	High	Medium	Conversion optimization	Medium
R10	High	High	Medium	High	Scaling strategy	Low
R11	High	High	High	High	Brand sustainability	Low

Table 2. System output and expert validation results

Scenario	Input Condition	Activated Rule	System Recommendation	Expert Match	Accuracy
S1	All Low	R1	Increase content & promotion	Yes	✓
S2	Mixed	R4	Improve targeting strategy	Yes	✓
S3	Medium	R6	Optimize posting frequency	Yes	✓
S4	Mixed High	R9	Improve conversion strategy	Yes	✓
S5	All High	R11	Maintain brand & scale	Yes	✓

The system was evaluated using multiple business scenarios to assess its ability to generate appropriate recommendations under different conditions. Table 2 illustrates the system's performance across different business condition scenarios. The results show that the system consistently activates the appropriate rule corresponding to each input configuration. In extreme conditions, such as S1 (all indicators low) and S5 (all indicators high), the system correctly triggers rules R1 and R11, generating recommendations aligned with foundational improvement and strategic sustainability, respectively. In mixed scenarios (S2–S4), the system demonstrates adaptability by selecting rules that reflect the combination of input variables rather than relying on a single dominant factor. Importantly, all system outputs fully match expert judgments, resulting in a 100% accuracy rate. This indicates that the rule-based reasoning mechanism effectively captures domain knowledge and applies it consistently across varying conditions.

The system achieves perfect scores in accuracy, precision, and conformity rate, indicating complete alignment between system-generated recommendations and expert decisions (see Table 3). Beyond correctness, the system also demonstrates high consistency, meaning that similar input conditions consistently produce the same outputs. Furthermore, the rule-based structure ensures high interpretability, as each recommendation can be directly traced to a specific rule in the knowledge base. These findings confirm that the system not only performs accurately but also fulfills key requirements of decision support systems, namely transparency, reliability, and usability.

Table 3. System performance metrics

Metric	Value
Accuracy	100%
Precision	100%
Conformity Rate	100%
Consistency	High
Interpretability	High

The results indicate that the proposed expert system is capable of generating adaptive, accurate, and context-sensitive marketing strategy recommendations based on varying performance conditions. The system demonstrates strong interpretability and transparency, as each output can be directly traced to specific rules within the knowledge base, while also effectively handling multi-variable inputs without oversimplification. Furthermore, the integration of priority levels enhances its practical usability, particularly for SMEs operating under resource constraints. Overall, the system successfully transforms digital performance indicators into structured and actionable recommendations, confirming its reliability, consistency, and applicability as a decision support tool in social commerce environments.

Discussion

The results confirm that the proposed forward chaining based expert system produces consistent, interpretable, and context-sensitive marketing strategy recommendations within social commerce environments. As emphasized by Rudin (2019) and further discussed by Rai (2020), interpretability plays a central role in decision support systems, particularly in contexts where user trust is essential. In this study, the alignment between system outputs and expert judgment indicates that the rule-based knowledge representation effectively captures domain expertise and translates it into structured decision logic. The transparency of the reasoning process, where each recommendation is directly linked to a specific rule, further reinforces the importance of explainable decision mechanisms in practical applications.

The forward chaining inference mechanism demonstrates strong suitability for data-driven decision environments characterized by measurable and dynamic performance indicators. According to Papadopoulos et al. (2022), rule-based systems provide explicit logical structures that enable traceable and deterministic reasoning processes, a perspective that is consistent with the findings of this study. The sequential activation of rules based on observable input conditions ensures logical consistency and reproducibility of outputs. Similarly, Navin and Krishnan (2024) highlight that rule-based inference mechanisms are particularly effective in domains requiring structured evaluation of multiple conditions, which is reflected in the system's ability to achieve complete agreement with expert validation.

The integration of multiple performance indicators into a unified rule-based structure enables a comprehensive interpretation of digital marketing performance. As noted by Zhao et al. (2023), social commerce research has frequently focused on isolated metrics, limiting the ability to derive holistic strategic insights. In contrast, this system synthesizes followers, engagement, promotion frequency, and conversion rate into a cohesive decision framework. This multidimensional integration enhances contextual relevance and reflects real-world business conditions more accurately, aligning with observations by Attar et al. (2022) regarding the need for integrated analytical approaches in digital commerce environments.

The differentiation of recommendations across performance levels demonstrates the system's capacity to support both operational improvement and strategic optimization. In line with the findings of Akter et al. (2022), advanced decision support systems are increasingly expected to generate prescriptive insights rather than purely descriptive outputs. The system's ability to produce stage-specific recommendations ranging from foundational improvements to strategic expansion also corresponds with the perspective of Alghamdi and Al-Baity (2022), who emphasize the role of data-driven systems in enabling strategic decision-making within digital business environments.

The incorporation of priority levels within the recommendation output introduces an additional layer of decision structuring, enabling users to evaluate the urgency and relative importance of actions. This structured prioritization enhances decision efficiency, particularly in SME contexts where resource allocation must be carefully managed. In this regard, the system extends conventional rule-based approaches by embedding a practical decision hierarchy that improves usability and implementation relevance.

The findings also reaffirm the continued relevance of interpretable models in decision support systems. While contemporary research often emphasizes complex machine learning approaches, Kruschel et al. (2026) argue that interpretability remains a critical requirement in many application domains. Consistent with this perspective, the present study demonstrates that high accuracy and consistency can be achieved through structured rule-based reasoning without reliance on opaque models. This reinforces the importance of balancing analytical capability with transparency in system design.

The knowledge base is constructed from a limited number of expert inputs, which may constrain its generalizability across broader contexts. In addition, the categorization of performance indicators into discrete levels introduces sensitivity to threshold selection, which may influence system adaptability. Future developments may consider integrating adaptive or hybrid mechanisms to enhance flexibility while preserving the interpretability inherent in rule-based systems.

CONCLUSION

This study develops and evaluates a forward chaining–based expert system for marketing decision support in social commerce environments by transforming digital performance indicators into structured and actionable recommendations. The results indicate that the system achieves high accuracy, consistency, and interpretability, with outputs closely aligned with expert judgment. The integration of multiple performance indicators within a rule-based framework enables the generation of context-aware and prioritized strategies, while the forward chaining mechanism ensures transparent and traceable reasoning. The inclusion of priority levels further supports effective decision-making, particularly for SMEs with limited resources. Overall, the system provides a reliable and interpretable tool that enhances the quality and consistency of data-driven marketing decisions.

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