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Research Article

Developing an AI-Driven Prescriptive Framework for Orchestrating MSME Supply and Demand: Integration of Hyper-Local Community Engagement Signals

Nanang Abdurahman[1*], Zainal Arifin Hasibuan[2], Irawan Afrianto[3], Ifan Dwiguna[4]

[1] Universitas Komputer Indonesia, Indonesia; e-mail: nanang.75725021@mahasiswa.unikom.ac.id
[2] Universitas Komputer Indonesia, Indonesia; e-mail: zhasibua@email.unikom.ac.id
[3] Universitas Komputer Indonesia, Indonesia; e-mail: irawan.afrianto@email.unikom.ac.id
[4] Universitas Komputer Indonesia, Indonesia; e-mail: irfan.dwiguna@email.unikom.ac.id
* Corresponding Author: Nanang Abdurahman

Abstract: Micro, Small, and Medium Enterprises (MSMEs) face significant challenges in balancing supply and demand amidst the rapid volatility of the digital economy era. This condition is primarily driven by conventional, reactive decision-making and a failure to utilize social media data beyond mere marketing metrics, resulting in operational inefficiencies such as overstocking or stockouts. This research aims to address this gap by developing an Artificial Intelligence-Based Prescriptive Framework for MSME Supply-Demand Orchestration. Adopting a Design Science Research (DSR) methodology, specifically focusing on problem identification, objective definition, and conceptual artifact design, this study synthesizes insights from 100 recent articles (2020-2025). The proposed conceptual artifact introduces a novel three-tier system architecture: a Sensing Layer utilizing NLP (BERT) to extract hyper-local community engagement signals into a Social Engagement Index (SEI), a Reasoning Layer employing a Hybrid Neuro-Fuzzy engine to accommodate MSME data sparsity, and a Prescriptive Actuation Layer. The findings present a mechanism that transforms unstructured qualitative social sentiment into quantitative, actionable logistical commands (e.g., "Priority Restock"), demonstrating superiority over existing predictive or macro-level models by offering a closed-loop, hyper-local solution. In conclusion, this research successfully formulates a framework that shifts MSME management paradigms from being purely reactive to actively responsive to social signals, theoretically expanding Social-SCM integration and practically offering a pathway to mitigate inventory risks and enhance economic sustainability.

Keywords: Artificial Intelligence; Community Engagement; Design Science Research; MSME; Prescriptive Analytics.

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1. Introduction

Background and Research Urgency

In the turbulent digital economy era, Micro, Small, and Medium Enterprises (MSMEs) face dual pressures: demands for operational efficiency and increasingly hard-to-predict market demand volatility [1], [2]. Digital transformation has become an imperative for MSME sustainability to maintain a competitive advantage [3]. However, unlike large firms possessing abundant data analytics resources, MSMEs are often trapped in reactive and intuitive decision-making, resulting in inefficiencies in supply chain management (SCM), such as overstocking or lost sales (stockouts) [4], [5].

The adoption of Industry 4.0 technologies, particularly Artificial Intelligence (AI), has proven to be a key driver of global supply chain performance [6], [7]. Recent literature indicates that AI can significantly improve demand forecasting accuracy compared to traditional statistical methods [7], [8]. Nevertheless, the greatest challenge for MSMEs is not merely predicting demand figures, but rather how to translate those predictions into precise operational decisions amidst the historical data sparsity they possess [9], [10].

Paradigm Shift: From Transaction Data to Social Signals

The Social Commerce phenomenon has fundamentally transformed the landscape of consumer interaction, where social media platforms are no longer merely marketing tools but have evolved into rich sources of market intelligence data [11], [12]. Empirical studies on MSMEs in developing countries, including Indonesia, demonstrate that social commerce acceptance is remarkably high [13]. Customer interactions in the form of reviews, comments, and engagement rates contain implicit signals regarding local market preferences and trends [14], [15].

Previous research has begun exploring the use of social media data for demand forecasting [16] and Machine Learning-based consumer behavior analysis [17]. Hoang et al. [11] assert that integrating social media into Supply Chain 4.0 practices is a crucial research trend. However, the majority of current approaches still treat social data merely as marketing variables [18], [19], and have not fully integrated them into technical logistics decision-making mechanisms [11].

Research Gap

Based on a systematic literature review, significant theoretical and practical gaps exist that motivate this research:

1) Dominance of Predictive Approaches vs. Absence of Prescriptive Ones: The majority of AI research in SCM focuses on predictive analytics (forecasting what will happen) [9], [20]. Very few studies develop prescriptive frameworks (recommending specific actions) for MSMEs, whereas MSMEs require concrete decision guidance to "orchestrate" supply and demand.
2) Big Data Bias vs. Small Data Reality: Existing AI models, such as LSTM or complex Deep Learning [21], [22], generally require large volumes of data rarely possessed by MSMEs. Hybrid approaches capable of handling small data uncertainty, such as Fuzzy Logic or expert systems [23], [24], have begun to be researched but have not been deeply integrated with real-time social sentiment analysis.
3) Void of Hyper-Local Integration: Studies on community engagement [25] are often separated from inventory optimization studies [23]. There is no comprehensive framework that specifically converts "hyper-local community engagement signals" into automated restocking decision parameters.

Research Questions

Departing from the urgency of the problem and the literature gaps outlined, this research focuses on answering the following three fundamental questions:

1) RQ1 (Empirical Validation): To what extent does community engagement data on hyper-local social platforms correlate with actual demand fluctuations in MSMEs?
2) RQ2 (Design & Artifact): How to design an Artificial Intelligence-based prescriptive mechanism capable of transforming unstructured social data into precise inventory decision parameters?
3) RQ3 (Performance Evaluation): How does the proposed AI-based orchestration framework theoretically compare to conventional management methods in terms of responsiveness and decision precision?

Research Objectives and Contributions

To bridge these gaps, this research aims to develop an Artificial Intelligence-Based Prescriptive Framework for MSME Supply-Demand Orchestration. This study proposes a novel approach integrating Natural Language Processing (NLP) for social signal extraction [26] with intelligent decision-making logic (Intelligent Decision Support System) [23], [27].

The novelty of this research lies in the mechanism of transforming qualitative data (local community sentiment) into quantitative decisions (inventory levels) through a hybrid system architecture. The contribution of this research is expected to enrich Social-SCM literature and provide a practical solution artifact for MSME resilience in the digital era.

2. Literature Review and Theoretical Foundation

Digital Transformation and AI Adoption in MSME Supply Chains

In the Industry 4.0 landscape, digital transformation has become a strategic imperative for Micro, Small, and Medium Enterprises (MSMEs) to maintain competitiveness [1], [2]. Current literature indicates a paradigm shift from basic digitalization towards the adoption of intelligent technologies (Artificial Intelligence/AI) [3], [4]. The role of AI in Supply Chain Management (SCM) is no longer limited to process automation but extends into the realm of predictive analytics and strategic decision-making [5], [6].

Despite its massive potential benefits, AI adoption in MSMEs faces unique challenges compared to large enterprises, particularly regarding resource constraints and data infrastructure readiness [7], [8]. Studies by Ayinaddis [3] and Toorajipour et al. [6] emphasize that the success of AI implementation in MSMEs is heavily contingent upon the organizational ability to integrate technology with existing business processes—an area often overlooked in purely technical literature.

The Evolution of Demand Forecasting: From Statistics to Social Analytics

Demand forecasting is a critical component in supply-demand orchestration. Traditional approaches relying on historical sales data (time-series) are increasingly considered inadequate for handling rapid market volatility [5], [9]. In response, researchers have begun exploring advanced Machine Learning algorithms, such as LSTM (Long Short-Term Memory) [10] and hybrid models [11], to improve prediction accuracy.

However, significant breakthroughs have emerged from the integration of "Social Big Data." Hoang et al. [12] and Wong et al. [13] identified that social media platforms have evolved into rich sources of market intelligence. Customer interactions in the form of reviews, comments, and engagement metrics contain implicit signals regarding consumer preferences that can precede actual sales trends [14], [15]. Frikha & Mrad [5] emphasize that AI-enabled demand forecasting utilizing this external data is capable of significantly reducing the bullwhip effect in global supply chains.

Community Engagement Analysis as a Predictor Variable

Empirical studies show that community engagement in the digital ecosystem correlates strongly with purchase intention and customer loyalty [16], [17]. Natural Language Processing (NLP) techniques and sentiment analysis, such as the use of BERT models, have proven effective in extracting insights from unstructured text data on review platforms and social media [18], [19].

Nevertheless, there is clear fragmentation in the literature. The majority of research utilizes this sentiment analysis exclusively for marketing and brand management purposes [20], [21], and rarely integrates it into logistics operational functions. Conversely, Karim et al. [22] proved that social media data can improve the forecasting accuracy of customer arrivals, which can logically be extrapolated to inventory forecasting.

Research Gap: Towards a Prescriptive Decision Support System

Based on the literature synthesis, three main gaps are identified that motivate this research:

1) Predictive Dominance vs. Prescriptive Scarcity: Most AI studies in SCM focus on predictive analytics (forecasting what will happen) [23], [24]. Very few studies develop prescriptive frameworks (recommending specific actions) for MSMEs. Yet, MSMEs require tactical decision guidance such as when to restock or hold inventory rather than just forecast figures [25].
2) Need for Hybrid Approaches for Small Data: Complex Deep Learning models are often unsuitable for MSMEs possessing limited data (data sparsity). Hybrid approaches such as Fuzzy Logic or expert systems, as suggested by Deb et al. [26] and Gutiérrez et al. [27], offer more adaptive solutions but have not been deeply explored in the context of real-time social data integration.
3) Absence of Hyper-Local Integration: Studies on engagement are often macro-scale. There is no comprehensive framework that specifically converts "hyper-local community engagement signals" into automated inventory decision parameters, despite the local context being crucial for MSMEs [8], [17].

Proposed Conceptual Framework

This research aims to bridge these gaps by proposing a prescriptive supply-demand orchestration framework. This framework is constructed upon the theoretical foundations of Demand-Driven Supply Chain [28] and Social Commerce Adoption [17].

Unlike conventional linear models, this study proposes a closed-loop model where social signals (Input) are processed through a hybrid intelligence layer (Hybrid AI Processing) combining NLP for sensing [18] and Fuzzy Logic for reasoning [26] to generate precise logistics decisions (Output). This approach shifts the position of community engagement data from mere marketing metrics to critical operational variables [12], [13].

3. Research Methodology

Research Design

This study adopts the Design Science Research (DSR) approach to develop a technological artifact relevant to the practical needs of MSMEs. This approach was chosen because the complexity of supply chain problems in MSMEs requires solutions that are not merely explanatory, but also prescriptive in the form of a Decision Support System, as suggested by Madanchian & Taherdoost [27] and Deb et al. [23] in the context of strategic information systems development.

Consistent with the DSR process model, this research is explicitly limited to the first three phases of the intelligent system development cycle: (1) Problem Identification, (2) Definition of Objectives, and (3) Design & Development of the Conceptual Artifact. Given the scope of this study as a foundational framework, the research focuses on the Design Cycle to construct a rigorous conceptual model, leaving the instantiation and full empirical evaluation for future research iterations. This structure ensures that the proposed AI model possesses a strong theoretical validity foundation before being implemented in resource-constrained MSME environments [3], [6].

Data Source and Knowledge Base

As the foundation for artifact design (Rigor Cycle), this research utilizes secondary data obtained through a Systematic Literature Review (SLR). This method has proven effective in mapping AI technology trends in supply chain management, as performed by Toorajipour et al. [5] and Shrivastav & Bag [6].

The knowledge base is constructed from an analysis of 100 reputable journal articles published between 2020 and 2025. To ensure a rigorous knowledge base, the literature selection followed a systematic protocol. The initial search was conducted primarily on the Scopus databases utilizing a combined search string: ("Artificial Intelligence" OR "Machine Learning" OR "Fuzzy") AND ("Supply Chain" OR "Inventory") AND ("SME" OR "MSME") AND ("Social Media" OR "Community Engagement"). The inclusion criteria were strictly limited to peer-reviewed journal articles published in English between 2020 and 2025 to capture post-pandemic technological dynamics.

After filtering out contextually irrelevant papers, duplicates, and non-peer-reviewed materials, a final set of 100 core articles was selected for the in-depth thematic and bibliometric analysis. This time range was selected to capture post-pandemic technology adoption dynamics [7] and the latest developments in Machine Learning algorithms [8], [9]. Inclusion criteria focused on articles discussing the integration of Artificial Intelligence, Community Engagement, and SME Operations to guarantee data relevance.

Research Process

The research procedure was executed through the following systematic stages:

Stage 1: Problem Identification

This stage deconstructs the problem of MSME operational inefficiency based on the literature review. In-depth analysis reveals a fragmentation (silo) between digital marketing analytics and logistics operational decisions [10]. Although social media data is acknowledged to be rich in consumer preference insights [11], [12], its utilization often stops at marketing strategies [13], [14], without integration into automated inventory management systems. The core problem is defined as the absence of a mechanism capable of transforming engagement signals into supply chain decision parameters.

Stage 2: Define Objectives

Based on the identified problem, the research establishes functional specifications for the developed artifact. The designed solution must meet the following criteria:

1) Prescriptive: Capable of providing specific action recommendations to mitigate overstock/stockout risks, surpassing the capabilities of standard predictive models [15], [16].
2) Hyper-Local: Capable of capturing demand signals from micro-communities, given the importance of local context for MSME sustainability [17], [18].
3) Adaptive: Utilizing a hybrid approach (Hybrid AI) tolerant of data sparsity, such as the Fuzzy Logic approach recommended by Deb et al. [2] and Gutiérrez et al. [19].

Stage 3: Design & Development

At this stage, the Conceptual Framework is constructed through logic modeling synthesis. The system design integrates two main components:

1) Sensing Mechanism: Adapting Natural Language Processing (NLP) concepts based on BERT [20] to extract sentiment and trends from unstructured data on social media.
2) Reasoning Mechanism: Designing supply-demand orchestration logic that connects community engagement variables as leading indicators with logistics decision variables [21], [22].

Analysis Instrument

To validate the research gap and novelty position, bibliometric analysis was conducted using VOSviewer software. This approach is commonly used to visualize the intellectual structure and research trends in the field of retail analytics and MSMEs, as applied by Ayinaddis [23] and Velásquez-Henao [24]. This analysis maps dominant topic clusters to ensure that the proposed artifact fills an untouched research gap (white space) in the current Social-SCM literature.

4. Results and Discussion

This section presents the primary output of the Design Science Research (DSR) cycle: the Prescriptive Framework for MSME Supply-Demand Orchestration. This artifact is designed to address data fragmentation identified in the literature review by integrating hyper-local social signals into operational decision-making mechanisms.

Intelligent Orchestration System Architecture

Based on the synthesis of Cluster A (Forecasting) and Cluster B (Social Analytics) literature, this research proposes a three-tier system architecture connecting the social ecosystem with the supply chain ecosystem. This architecture is designed in a modular fashion to ensure scalability for MSMEs [1], [2].

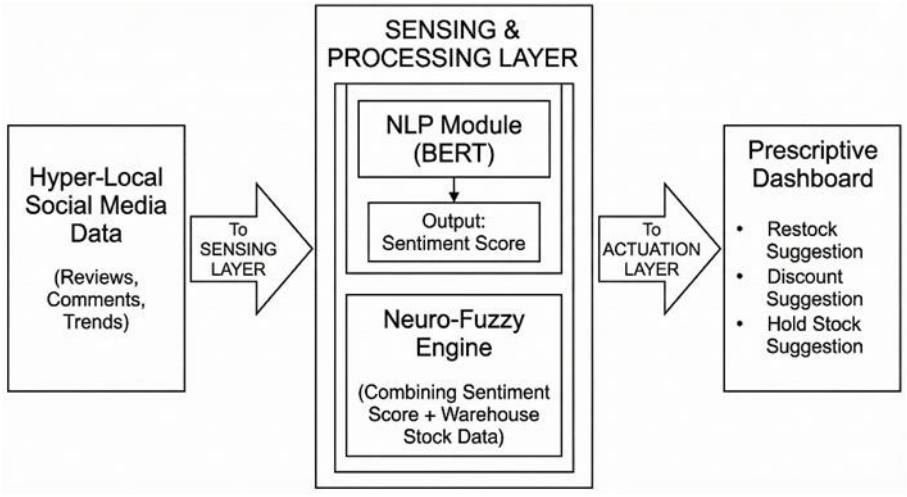


Figure 1. Proposed System Architecture (Proposed Framework).

The architecture comprises three primary components:

Sensing Layer:

This component functions as a "digital sensor" capturing market signals in real-time. Unlike conventional approaches relying solely on historical transaction data [1], this layer employs BERT-based Natural Language Processing (NLP) algorithms [2] to mine unstructured data from local social media platforms. The extracted data encompasses discussion volume, comment sentiment, and geo-specific search trends (hyper-local trends) [3], [4].

Reasoning Layer:

This represents the system's intelligence core (brainware). Considering the historical data limitations (data sparsity) in MSMEs, this system does not employ pure Deep Learning models that necessitate Big Data [5], [6], but instead adopts a Hybrid Neuro-Fuzzy approach. This algorithm was selected for its capability to map human language ambiguity (e.g., "this product is going viral") into precise quantitative parameters, as its effectiveness was validated in an MSME inventory study by Deb et al. [7].

Actuation Layer:

Unlike traditional Decision Support Systems (DSS) which are merely descriptive or predictive [8], [9], this layer is prescriptive. The generated output is not merely trend charts, but automated tactical action recommendations such as "Restock Immediately" or "Activate Flash Sale" to maintain supply and demand orchestration balance.

Data Transformation Mechanism: From Social Signals to Logistics Decisions

The primary novelty of this framework lies in the data transformation mechanism. The system converts qualitative unstructured data into quantitative decision parameters through a systematic logic flow, detailed as follows:

Stage 1: Social Signal Quantification (The SEI Model)

Raw data extracted from social media platforms (comments, reviews, shares) are processed to generate the Social Engagement Index (SEI). To ensure reproducibility and transparency, the SEI is calculated using a weighted composite formula that integrates three critical dimensions: Volume (intensity of discussion), Velocity (speed of viral spread), and Valence (net sentiment score). The mathematical representation of the SEI is proposed as follows:

$$SEIp = (w1 \times Nvol) + (w2 \times Vvel) + (w3 \times Snet)$$

Where:

SEI_p : Social Engagement Index for a specific Product (p).

N_{vol} : Normalized volume of mentions/interactions (scaled 0–1).

V_{vel} : Velocity or rate of change in mentions over a specific time window (Δt).

S_{net} : Net sentiment score (ratio of Positive minus Negative interactions).

$W_{1,2,3}$: Weighting coefficients assigned based on the MSME's strategic priority (e.g., prioritizing viral speed over volume).

In practical MSME implementation, these weighting coefficients (w1, w2, w3) are not static. Initially, they can be determined through expert judgment techniques, such as the Analytic Hierarchy Process (AHP), tailored to the MSME's specific business model (e.g., a fast-fashion brand might assign a higher weight to velocity, w2, to capture viral trends rapidly). In advanced iterations of this framework, these weights are designed to be dynamically optimized using machine learning algorithms that continuously adjust the coefficients based on historical forecasting accuracy and actual sales conversions.

Hypothetical Example:

Consider a local MSME fashion product that suddenly trends on social media. The system detects high interaction volume (Nvol =0.8), rapid viral spread (Vvel =0.9), and predominantly positive reviews (Snet =0.7). Assuming equal weights (w=0.33), the calculated SEI would be:

$$SEI = (0.33 \times 0.8) + (0.33 \times 0.9) + (0.33 \times 0.7) = 0.79$$

An SEI score of 0.79 (on a 0–1 scale) is classified as a "Strong Demand Signal," which serves as a leading indicator detecting potential sales surges 3–7 days before actual transactions occur.

Stage 2: Hybrid Inference (Neuro-Fuzzy Engine)

The calculated SEI value is subsequently input into the Adaptive Neuro-Fuzzy Inference System (ANFIS). Unlike rigid statistical models, this engine processes the SEI alongside internal inventory data using linguistic variables. The decision logic is governed by an empirical Rule Base, such as:

Rule 1: IF (SEI is High) AND (Warehouse Stock is Low) THEN (Decision is Priority Restock).

Rule 2: IF (SEI is Low) AND (Warehouse Stock is High) THEN (Decision is Discount Promotion).

Rule 3: IF (SEI is High) AND (Warehouse Stock is High) THEN (Decision is Hold Price/Maximize Margin).

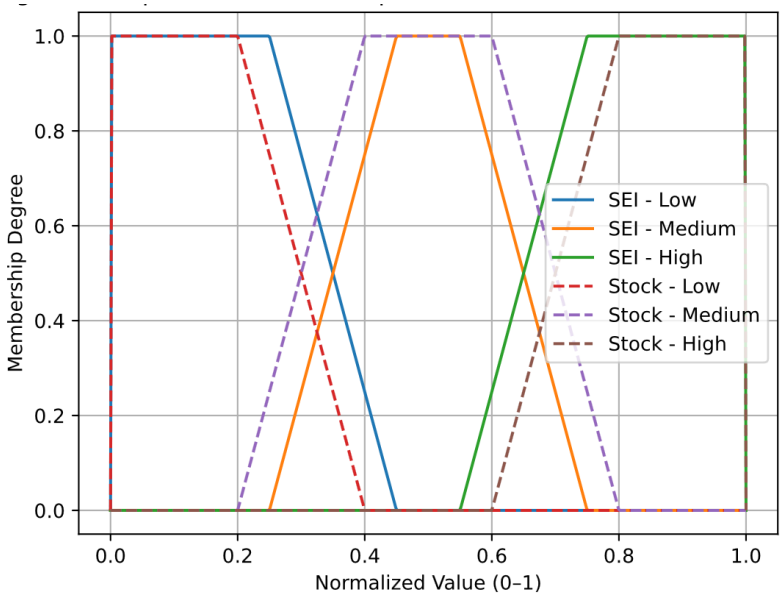


Figure 2: Trapezoidal Membership Functions for SEI and Warehouse Stock Variables

To computationally process these rules, the linguistic variables (e.g., Low, Medium, High) are mathematically represented using trapezoidal membership functions (as illustrated in Figure 2). For instance, the calculated SEI score is mapped onto a degree of membership (⌈) ranging from 0 to 1. This fuzzification process is critical; it allows the system to handle the inherent ambiguity of human social sentiment and translate it into a crisp logistical command during the defuzzification stage (e.g., Center of Gravity method). This reasoning layer provides a resilient approach against MSME data sparsity, acting as a bridge between qualitative social buzz and quantitative inventory levels.

The linguistic variables (Low, High) are defined using trapezoidal membership functions based on historical data distribution quartiles. For instance, SEI is classified as 'High' if the calculated score exceeds the 75th percentile of the rolling 30-day engagement average.

This hybrid approach allows the system to map the ambiguity of human language (e.g., "this product is viral") into precise logistical actions, overcoming the limitations of conventional models that fail to respond to fluid market dynamics [12], [13].

Theoretical Validation and Comparative Analysis

To validate the superiority of the proposed artifact, a comparative analysis was conducted against existing models in the literature (Table 1).

Table 1. Comparison of the Proposed Model with Previous Research

Comparative Dimension	Conventional Model	Social Marketing Model	Proposed Model (Proposed Framework)
Main Focus	Demand Volume Prediction *(Forecasting)*	Branding & Customer Loyalty *(Marketing)*	Supply-Demand Orchestration *(Balancing) via Social Signals*
Nature of Decision	**Predictive (Passive)** *(Informs "what will happen")*	**Descriptive (Analytical)** *(Informs "who likes it")*	**Prescriptive (Active/Actionable)** *(Commands "restock now")*
Data Source	Internal Data (*Historical Transactions)*	External Data *(Social Media)*	**Hybrid Integration** *(Combined Internal & Social Signals)*
AI Technology	Statistical / Complex Deep Learning *(Requires Big Data)*	NLP / Sentiment Analysis *(Text Only)*	**Hybrid Neuro-Fuzzy** *(Explainable AI & Small Data Tolerant)*
Granularity Level	Macro / Global	General / Brand-Level	**Hyper-Local** *(Community/District Level)*
Connectivity	Open-Loop *(Output stops at reports)*	Open-Loop *(Output stops at ad strategy)*	**Closed-Loop** *(Output directly drives logistics)*

The analysis of the table above demonstrates that the proposed framework addresses a significant white space in the existing literature. Frikha's model [7] excels in accuracy but lacks depth regarding the social data context. Conversely, Arista's model [13] demonstrates strength in social analysis yet remains disconnected from logistics decision-making. The proposed framework bridges this gap by establishing a closed-loop system wherein social signals directly drive supply chain decisions [3].

Simulated Use Case (Proof of Concept)

To theoretically demonstrate the artifact's utility and prescriptive power, a simulated scenario is presented involving a local MSME experiencing a sudden demand shock.

1) Scenario Parameters: A local fashion product gains sudden traction on TikTok. The Sensing Layer calculates an SEI score of 0.85 (Categorized as High). The current warehouse stock is 20 units (Categorized as Low). The production lead time is 5 days.
2) Conventional Model Response (Predictive/Historical): Traditional systems analyze the past month's sales data, which were flat. The system forecasts stable demand and recommends No Action. Result: The MSME experiences severe stockouts on Day 3 of the viral trend, losing significant potential revenue and customer trust.
3) Proposed AI-Driven Framework Response (Prescriptive/Hybrid): The Sensing Layer detects the SEI spike on Day 1. The Neuro-Fuzzy Reasoning Layer processes the active rule: IF (SEI is High) AND (Warehouse Stock is Low). The Actuation Layer instantly outputs a prescriptive command on the dashboard: "Priority Restock: Initiate emergency production of 100 units immediately". Result: The MSME captures the demand peak perfectly, avoiding stockouts while maximizing profit margins.

This simulation highlights the framework's capability to act as an early-warning and action-generation system, validating its superiority over passive forecasting models.

Managerial Implications for MSMEs

The implementation of this framework offers significant practical implications for MSME resilience. By leveraging "digital neighbors" as sources of market intelligence, MSMEs can transition from reactive to responsive management models [4]. This system enables MSMEs to mitigate the risk of dead stock accumulation resulting from sudden trend shifts, while simultaneously minimizing lost sales opportunities during product virality events, thereby supporting their economic sustainability in the era of digital competition [5], [6].

5. Conclusion and Implications

Conclusion

This study successfully identifies and bridges a critical fragmentation within the MSME supply chain management literature: the disconnect between digital marketing analytics and operational decision-making. Based on a synthesis of 100 recent articles (2020–2025) utilizing the Design Science Research (DSR) approach, this study concludes that conventional forecasting methods relying solely on historical data are no longer adequate for addressing market volatility in the social commerce era.

The primary contribution of this research is the development of a Prescriptive Framework for Supply-Demand Orchestration, a conceptual artifact that positions hyper-local community engagement signals as the primary predictor variable. Unlike previous models which are passive (predictive) in nature, the proposed framework is active (prescriptive), enabling MSMEs to automatically convert unstructured market sentiment into precise logistics decisions. This shifts the MSME management paradigm from "reactive to sales" to "responsive to social signals."

Managerial and Theoretical Implications

Theoretically, this research expands the Social-SCM discourse by demonstrating that the concept of Community Engagement is not only relevant to marketing but constitutes a vital logistics intelligence asset. Managerially, this framework offers guidance for MSME owners to move beyond viewing social media merely as a promotional storefront, and instead recognize it as an early demand sensor capable of preventing the risks of overstocking and lost sales.

6. Limitations and Future Work

Research Limitations

As a conceptual artifact design study, the primary limitation of this research lies in the absence of full-scale empirical validation. Current validation is limited to theoretical grounding and literature synthesis (rigor cycle), thus the model's effectiveness in real-world operational environments has not yet been quantitatively measured. Furthermore, this framework assumes operation within an ideal digital infrastructure, which may not be fully available to MSMEs in regions with a high digital divide.

Future Research Agenda (Future Work)

To develop this framework into a mature practical solution, future researchers are advised to focus on the following areas:

1) Empirical Validation and Prototyping: Developing a software prototype based on the proposed architecture and testing it in real-world MSME case studies using experimental methods (A/B Testing) to measure improvements in forecasting accuracy compared to traditional methods.
2) Hybrid Algorithm Comparison: Conducting technical comparative studies to determine the most efficient AI algorithm combination for MSMEs. Future research could compare the performance of Adaptive Neuro-Fuzzy Inference System (ANFIS) versus Lightweight Deep Learning in terms of accuracy versus computational cost.
3) Multi-Platform Integration: Expanding the sensing layer's capabilities to not only retrieve data from a single social media platform but to aggregate signals from diverse sources (omnichannel signals), including marketplaces and instant messaging applications, to obtain a more holistic demand picture.

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