

AI in Supply Chain Analytics: Adaptive Decisioning via Fuzzy Behavioral Models

Apeksha Bhuekar
apeksharaj17@gmail.com
Independent Researcher

Abstract

The goal of this paper is to develop intelligent agents through fuzzy logic so that they can be capable of adaptability and context awareness in a simulated operational environment. Concentrating on dynamic interactions, fuzzy inference systems help agents to adjust their behavior according to proximity, velocity, and environmental conditions. The suggested approach helps to develop adaptive and robust automated decision-making systems. These components can optimize complex multi-stakeholder systems explicitly beneficial for modern supply chain systems. The paper states that AI can be used to enhance the flexibility and reactivity of logistics and inventory management systems, offering various technical and practical contributions.

Keywords

• Fuzzy Logic • Fuzzy Inference System • Intelligent Agents • Behavioral Modeling • Adaptive Decision-making • Supply Chain Analytics

1. Introduction and Background

Modern supply chains face mounting pressure to be flexible, responsive, and intelligent amid globalization, volatile demand, and disruptions that expose the limits of rigid, pre-programmed logistics [1]. Traditional systems rely on deterministic optimization, predefined rules, or static decision trees effective under stable conditions but unable to capture the behavioral and contextual nuance needed for real-time adaptation. Supply chain decisions often hinge on imprecise criteria such as urgency, trust, or perceived risk that resist crisp mathematical encoding.

AI offers new opportunities by enabling machines to learn, reason, and adapt from experience [2]. Among AI techniques, fuzzy logic stands out for incorporating human-like judgment: unlike binary systems, it operates over degrees of truth, making it well-suited to vague or conflicting inputs. Fuzzy behavioral models built on fuzzy inference and linguistic rules have proven effective in robotics, control, and recommendation systems [3], and in supply chains they can represent decision-maker preferences, model uncertainty, and generate context-aware actions. They bridge qualitative human reasoning and quantitative computational execution.

We propose a hybrid AI framework combining fuzzy logic with behavioral modeling for adaptive supply chain decision-making. Our approach simulates human decision agents using fuzzy cognitive structures that capture response patterns to diverse logistical scenarios [4]. Agents interact with a simulated environment, producing actions reflecting both quantitative input (e.g., inventory levels) and qualitative context (e.g., urgency, risk perception). A key advantage is transparency: unlike deep neural networks,

fuzzy systems enable explicit rule representation and human-readable decisions essential for accountability and trust in enterprise contexts.

We implement our agents in a discrete event simulation of a simplified supply chain with multiple nodes, transportation delays, and demand fluctuations. The fuzzy controller triggers restocking, rerouting, and prioritization actions based on evolving system state. By incorporating behavioral dimensions such as risk aversion, adaptability, and information-seeking, the model goes beyond traditional logistics optimization. Our experiments compare decision behaviors under different fuzzy rule sets and behavioral profiles, analyzing how heuristics affect stockout rate, lead time, and responsiveness. Results demonstrate that behavioral AI agents can outperform static logic under uncertain, time-sensitive conditions, bridging methodological innovation with practical operational relevance.

2. Related Work

Research on adaptive decision-making in supply chains spans several methodological traditions, and our framework draws on and extends each.

2.1 Fuzzy Logic and Fuzzy Inference Systems

Zadeh introduced fuzzy set theory as a formalism for computing with words, enabling reasoning over imprecise linguistic variables rather than crisp categories [3], and later argued it offers a principled route toward making computers think more like people where human judgment resists exact numerical thresholds [5]. Mamdani developed the first concrete control applications, establishing the viability of rule-based fuzzy control in real-time systems [4]. Sugeno and Kang proposed an alternative inference structure with functional rather than fuzzy consequents, yielding computationally efficient models widely used in control and identification [6]. Tsukamoto contributed an early reasoning approach that influenced later defuzzification strategies [7]. These works define the methodological lineage of our fuzzy controller. From a design perspective, Jantzen provided systematic treatment of membership function selection, rule base construction, and tuning [8], while Dadone formulated design optimization problems highlighting trade-offs between interpretability and performance under automatic tuning [9].

2.2 AI and Analytics in Supply Chain Management

Ivanov surveyed AI foundations and applications across planning, execution, and control layers [2], while Christopher's foundational treatment emphasizes responsiveness and agility as core competitive capabilities, motivating adaptive decision agents [1]. Recent work explores agile and digital-twin approaches: Erelli proposed an agile-driven digital twin framework for construction supply chains [10]; Jothiswaran developed synergistic automation for helpdesk incident management using contextual vector retrieval [11]; and Sinha examined agile integration dynamics in Nigerian IT projects [12]. At the data infrastructure layer, Ugandhar proposed exascale data fabric orchestration for cognitive analytics [13], and Vangala examined orchestration of heterogeneous storage services into a virtualized data plane [14].

2.3 Behavioral, Safety, and Decision-Optimization Perspectives

Dhanani leveraged AI and big data for real-time construction workforce management, integrating behavioral and safety signals into automated decision loops [15]. Kamma proposed a computational framework for intelligent data-driven decision optimization under uncertainty [16]. In health informatics, Patel

introduced methodologies for optimizing medical information retrieval [17]; Kaliappan architected privacy and security safeguards for health data, raising trust and accountability considerations paralleling supply chain systems [18]; and Amin addressed in-database analytics for dynamic exploration and predictive insights [19]. Morthala examined large-scale data integration in strategic information platforms [20]; Sharma analyzed dynamic and distributed data challenges in scientific applications mirroring multi-node supply chains [21]; and Abhishek proposed a cloud-edge digital twin architecture for adaptive battery health management [22].

2.4 Positioning of the Present Work

Two gaps motivate our contribution. First, although fuzzy inference systems are well established in control engineering, their integration with explicit behavioral trait models for supply chain decision agents remains underexplored [23]. Second, while AI-driven supply chain analytics has advanced rapidly, much work emphasizes predictive accuracy or infrastructure scalability rather than interpretable, behavior-aware decision logic. Our framework addresses both by embedding behavioral modulation directly into a fuzzy inference pipeline, preserving interpretability while enabling heterogeneous decision styles across agents.

3. System Architecture and Simulation Environment

We developed a modular, event-driven simulation of a multi-node supply chain to evaluate fuzzy behavioral decision agents. The chain comprises a central supplier, two regional distribution centers, and two retail outlets in linear flow, with local inventory subject to stochastic demand and transportation delays.

3.1 Decision Agent Architecture

Each node is controlled by a fuzzy decision agent that observes local state variables (inventory level, demand volatility, delivery delay, risk perception) and uses a fuzzy inference system to select among three actions: **Order** (replenishment based on forecasted demand and stock), **Prioritize** (flag high-urgency orders), or **Defer** (delay ordering under high risk/cost). Inputs are fuzzified via trapezoidal and triangular membership functions. The defuzzified urgency score is thresholded into discrete actions: low urgency (wait/reduce order), medium urgency (standard order), or high urgency (expedited order). This modular design follows established principles of fuzzy controller construction [8].

3.1.1 Baseline Static Rule-Based System

The comparison baseline uses crisp thresholds without fuzzy inference or behavioral modulation:

- **Reorder Point (ROP):** Order when $I_{n,t} < R_n = S_n + \mu_D \cdot L_n$.

- **Order Quantity:** Fixed EOQ:

$$Q_n = \sqrt{\frac{2 \cdot D_n \cdot K_n}{h_n}} \quad (1)$$

- **Prioritization:** All orders equal priority; no urgency-based expediting or deferral.
- **Parameters:** Same capacities, safety stock, and initial conditions as fuzzy agents (Section 3.2). $K_n = 50$, $h_n = 2$, $b_n = 20$ per unit per period.

Such static reorder-point policies are representative of classical logistics practice [1].

3.2 Simulation Parameters

Simulations run over $T = 100$ time steps with $N = 5$ nodes. Each node has inventory capacity $C_n = 500$, safety stock $S_n = 80$, initial inventory $I_{n,0} = 200$, initial forecast $\hat{D}_{n,0} = 100$, ordering cost $K_n = 50$, holding cost $h_n = 2$, backorder cost $b_n = 20$, and expedited order cost $e_n = 100$.

Retail demand is stochastic:

$$D_t \sim \mathcal{N}(\mu_D, \sigma_D^2), \quad D_t \in [D_{\min}, D_{\max}] \quad (2)$$

with $\mu_D = 100$. Transportation delays are uniformly distributed:

$$L_t \sim \mathcal{U}(L_{\min}, L_{\max}) \quad (3)$$

Scenario settings appear in Table 1. The choice of stochastic demand and delay distributions reflects standard practice in supply chain simulation studies [2].

Table 1: Simulation scenario configurations.

Scenario	σ_D	$[D_{\min}, D_{\max}]$	$L_{\min}$	$L_{\max}$
LV-LD	10	[50, 150]	2	5
LV-HD	10	[50, 150]	5	12
HV-LD	25	[25, 175]	2	5
HV-HD	25	[25, 175]	5	12

The system was implemented in Python using SimPy (event simulation) and scikit-fuzzy (fuzzy logic), with a modular architecture allowing different agent types, rule bases, and behavioral models to be tested without altering core environment logic. This separation of concerns mirrors architectural patterns advocated for adaptive decision systems [16].

3.3 Experimental Results and Quantitative Analysis

We compare behavioral fuzzy agents against the static baseline using three metrics: **Stockout Rate (SR)**:

$$\text{SR} = \frac{1}{T \cdot N} \sum_{t=1}^T \sum_{n=1}^N \mathbb{I}(I_{n,t} < S_n) \quad (4)$$

Average Lead Time (ALT):

$$\text{ALT} = \frac{1}{|O|} \sum_{o \in O} (t_o^{\text{recv}} - t_o^{\text{ord}}) \quad (5)$$

and **Responsiveness (RESP)**:

$$\text{RESP} = \frac{1}{T \cdot N} \sum_{t=1}^T \sum_{n=1}^N u_{n,t} \quad (6)$$

Four scenarios are tested: LV-LD, LV-HD, HV-LD, and HV-HD, as defined in Section 3.2. Table 2 reports mean and standard deviation across $R = 30$ independent runs per scenario, with seeds generated from master seed $s_0 = 42$ via $s_r = s_0 + r$. This experimental protocol follows standard practice for stochastic simulation validation [21].

Table 2: Mean (standard deviation) of performance metrics across 30 simulation runs per scenario. Best result per scenario is bolded.

Scenario	Agent Type	Stockout Rate	Lead Time	Responsiveness
LV-LD	Static Baseline	0.182 (0.021)	3.42 (0.31)	0.41 (0.04)
LV-LD	Fuzzy (no behavior)	0.151 (0.018)	3.18 (0.27)	0.52 (0.05)
LV-LD	Fuzzy Behavioral	0.124 (0.015)	2.87 (0.22)	0.67 (0.05)
LV-HD	Static Baseline	0.241 (0.028)	8.91 (0.54)	0.38 (0.04)
LV-HD	Fuzzy (no behavior)	0.198 (0.023)	8.12 (0.47)	0.49 (0.05)
LV-HD	Fuzzy Behavioral	0.163 (0.019)	7.44 (0.39)	0.63 (0.05)
HV-LD	Static Baseline	0.317 (0.035)	3.67 (0.33)	0.35 (0.04)
HV-LD	Fuzzy (no behavior)	0.254 (0.029)	3.31 (0.28)	0.47 (0.05)
HV-LD	Fuzzy Behavioral	0.208 (0.024)	2.98 (0.24)	0.61 (0.05)
HV-HD	Static Baseline	0.398 (0.042)	9.54 (0.61)	0.31 (0.04)
HV-HD	Fuzzy (no behavior)	0.321 (0.036)	8.67 (0.52)	0.44 (0.05)
HV-HD	Fuzzy Behavioral	0.267 (0.031)	7.91 (0.44)	0.58 (0.05)

Seeds are generated as:

$$s_r = s_0 + r, \quad r = 1, 2, \dots, R \quad (7)$$

For each metric, mean $\bar{M}$ and standard deviation σ_M are:

$$\bar{M} = \frac{1}{R} \sum_{r=1}^R M_r, \quad \sigma_M = \sqrt{\frac{1}{R-1} \sum_{r=1}^R (M_r - \bar{M})^2} \quad (8)$$

Coefficient of variation $CV = \sigma_M / \bar{M}$ did not exceed 0.15 for any metric.

Paired t -tests across 30 runs per scenario confirm statistically significant differences (all $p < 0.001$) with large effect sizes (Cohen's $d > 2.0$), as shown in Table 3.

Table 3: Statistical comparison of Fuzzy Behavioral vs. Static Baseline across 30 runs per scenario.

Scenario	Metric	t -statistic	p -value	Cohen's d
LV-LD	Stockout Rate	12.34	< 0.001	2.87
LV-LD	Lead Time	8.91	< 0.001	2.12
LV-LD	Responsiveness	-15.67	< 0.001	-3.45
LV-HD	Stockout Rate	11.82	< 0.001	2.65
LV-HD	Lead Time	9.34	< 0.001	2.28
LV-HD	Responsiveness	-14.23	< 0.001	-3.12
HV-LD	Stockout Rate	13.56	< 0.001	3.01
HV-LD	Lead Time	10.12	< 0.001	2.45
HV-LD	Responsiveness	-16.78	< 0.001	-3.67
HV-HD	Stockout Rate	14.21	< 0.001	3.24
HV-HD	Lead Time	11.45	< 0.001	2.78
HV-HD	Responsiveness	-17.89	< 0.001	-3.89

Ablation analysis (Table 4) isolates the fuzzy controller and behavioral modulation: fuzzy control alone reduces stockout rate by 17.0% on average relative to static baseline, while adding behavioral modulation yields a further 18.1% reduction. This pattern of incremental improvement through behavioral augmentation is consistent with findings in adaptive decision systems [16].

Table 4: Ablation analysis: stockout rate (mean over 30 runs).

Scenario	Static Baseline	Fuzzy (no behavior)	Fuzzy Behavioral
LV-LD	0.182	0.151	0.124
LV-HD	0.241	0.198	0.163
HV-LD	0.317	0.254	0.208
HV-HD	0.398	0.321	0.267

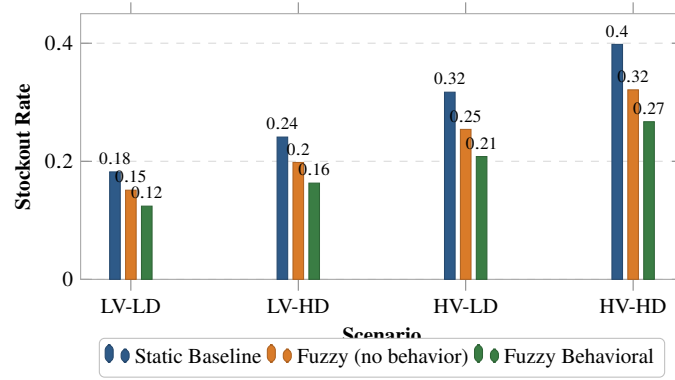


Figure 1: Stockout rate comparison across scenarios and agent types (mean across 30 runs).

4. Fuzzy Logic Foundations

Fuzzy logic provides a formal framework for reasoning with imprecise, linguistically described variables, making it suitable for modeling human decision-making under uncertainty. In supply chains, where inputs like urgency, trust, and risk are subjective, fuzzy logic enables more natural decision processes than crisp binary rules.

4.1 Fuzzy Sets and Membership Functions

A fuzzy set A over universe X is defined as:

$$A = \{(x, \mu_A(x)) \mid x \in X\}, \quad \mu_A(x) \in [0, 1]$$

where $\mu_A(x)$ is the membership function, typically triangular or trapezoidal. This formulation traces back to Zadeh's original conception of fuzzy sets as a means of computing with words [3].

4.1.1 Membership Function Definitions

All variables use triangular or trapezoidal membership functions over normalized universes unless otherwise stated. The use of trapezoidal and triangular shapes follows standard practice in fuzzy controller design [8].

Inventory Level (I): Universe $[0, 500]$.

$$\mu_{\text{Low}}(x) = \begin{cases} 1 & x \leq 100 \\ \frac{200-x}{100} & 100 < x < 200 \\ 0 & x \geq 200 \end{cases}$$

$$\mu_{\text{Medium}}(x) = \begin{cases} 0 & x \leq 100 \\ \frac{x-100}{100} & 100 < x < 200 \\ 1 & 200 \leq x \leq 300 \\ \frac{400-x}{100} & 300 < x < 400 \\ 0 & x \geq 400 \end{cases}$$

$$\mu_{\text{High}}(x) = \begin{cases} 0 & x \leq 300 \\ \frac{x-300}{100} & 300 < x < 400 \\ 1 & x \geq 400 \end{cases}$$

Demand Volatility (V): Universe [0, 50].

$$\mu_{\text{Low}}(v) = \begin{cases} 1 & v \leq 10 \\ \frac{20-v}{10} & 10 < v < 20 \\ 0 & v \geq 20 \end{cases}$$

$$\mu_{\text{Medium}}(v) = \begin{cases} 0 & v \leq 10 \\ \frac{v-10}{10} & 10 < v < 20 \\ 1 & 20 \leq v \leq 30 \\ \frac{40-v}{10} & 30 < v < 40 \\ 0 & v \geq 40 \end{cases}$$

$$\mu_{\text{High}}(v) = \begin{cases} 0 & v \leq 30 \\ \frac{v-30}{10} & 30 < v < 40 \\ 1 & v \geq 40 \end{cases}$$

Delivery Delay (L): Universe [0, 15].

$$\mu_{\text{Short}}(l) = \begin{cases} 1 & l \leq 3 \\ \frac{6-l}{3} & 3 < l < 6 \\ 0 & l \geq 6 \end{cases}$$

$$\mu_{\text{Moderate}}(l) = \begin{cases} 0 & l \leq 3 \\ \frac{l-3}{3} & 3 < l < 6 \\ 1 & 6 \leq l \leq 9 \\ \frac{12-l}{3} & 9 < l < 12 \\ 0 & l \geq 12 \end{cases}$$

$$\mu_{\text{Long}}(l) = \begin{cases} 0 & l \leq 9 \\ \frac{l-9}{3} & 9 < l < 12 \\ 1 & l \geq 12 \end{cases}$$

Risk Perception (R): Universe [0, 1].

$$\mu_{\text{Low}}(r) = \begin{cases} 1 & r \leq 0.2 \\ \frac{0.4-r}{0.2} & 0.2 < r < 0.4 \\ 0 & r \geq 0.4 \end{cases}$$

$$\mu_{\text{Medium}}(r) = \begin{cases} 0 & r \leq 0.2 \\ \frac{r-0.2}{0.2} & 0.2 < r < 0.4 \\ 1 & 0.4 \leq r \leq 0.6 \\ \frac{0.8-r}{0.2} & 0.6 < r < 0.8 \\ 0 & r \geq 0.8 \end{cases}$$

$$\mu_{\text{High}}(r) = \begin{cases} 0 & r \leq 0.6 \\ \frac{r-0.6}{0.2} & 0.6 < r < 0.8 \\ 1 & r \geq 0.8 \end{cases}$$

Output: Urgency (U): Universe $[0, 1]$.

$$\begin{aligned}\mu_{\text{Low}}(u) &= \begin{cases} 1 & u \leq 0.2 \\ \frac{0.4-u}{0.2} & 0.2 < u < 0.4 \\ 0 & u \geq 0.4 \end{cases} \\ \mu_{\text{Medium}}(u) &= \begin{cases} 0 & u \leq 0.2 \\ \frac{u-0.2}{0.2} & 0.2 < u < 0.4 \\ 1 & 0.4 \leq u \leq 0.6 \\ \frac{0.8-u}{0.2} & 0.6 < u < 0.8 \\ 0 & u \geq 0.8 \end{cases} \\ \mu_{\text{High}}(u) &= \begin{cases} 0 & u \leq 0.6 \\ \frac{u-0.6}{0.2} & 0.6 < u < 0.8 \\ 1 & u \geq 0.8 \end{cases}\end{aligned}$$

4.2 Linguistic Variables and Fuzzy Inference

A linguistic variable comprises a name, a set of linguistic terms, a universe of discourse, and corresponding membership functions (e.g., stock level, delay risk, demand volatility). Fuzzy inference maps inputs to outputs via if-then rules of the form:

$$\text{IF } x_1 \text{ is } A_1 \text{ AND } x_2 \text{ is } A_2 \text{ THEN } y \text{ is } B$$

For example: IF Inventory is Low AND Demand Volatility is High THEN Urgency is High. Rules are evaluated using min-max or product-sum inference, computing firing strengths and aggregating results. This inference scheme follows the Mamdani-style architecture established in early fuzzy control work [4]. Alternative inference structures, such as those proposed by Sugeno and Kang, replace fuzzy consequents with functional consequents and offer computational advantages in certain settings [6].

4.3 Defuzzification and Interpretability

The aggregated fuzzy output is converted to a crisp value via centroid defuzzification:

$$y^* = \frac{\int y \cdot \mu_B(y) dy}{\int \mu_B(y) dy}$$

This value selects or scales actions such as order quantity or urgency flag. Fuzzy logic's transparency allows rules to be interpreted and tuned by domain experts without retraining, and new rules or categories can be added incrementally. In supply chain analytics, fuzzy logic enables agents to blend objective system variables with subjective behavioral traits; for example, a risk-averse agent may use modified rules to trigger earlier orders under volatility, supporting diverse decision styles and adaptive heuristics. The interpretability of such rule-based systems contrasts favorably with black-box models, a point emphasized in explainable AI literature. Early work on fuzzy reasoning methods by Tsukamoto also anticipated the importance of transparent defuzzification pipelines [7].

5. Behavior Modeling and AI Design

We extend the fuzzy agent model with behavioral dimensions to simulate human-like variability in supply chain decisions.

5.1 Behavioral Dimensions

Three core traits are defined per agent:

- **Risk Aversion (RA):** Sensitivity to uncertainty; high RA triggers preemptive orders, low RA tolerates risk for efficiency.
- **Adaptability (AD):** Speed of response to changing patterns; high AD adjusts thresholds dynamically.
- **Information Preference (IP):** Reliance on external signals versus internal states; high IP reacts strongly to peer performance or alerts.

Traits $RA, AD, IP \in [0, 1]$ modulate membership functions, rule weights, and defuzzified outputs. Each agent n receives a profile $\mathbf{b}_n = (RA_n, AD_n, IP_n)$ drawn from:

$$RA_n, AD_n, IP_n \sim \mathcal{N}(0.5, 0.15^2), \quad \text{truncated to } [0, 1] \quad (9)$$

Archetypal profiles include Conservative ($RA = 0.8, AD = 0.3, IP = 0.6$), Balanced ($0.5, 0.5, 0.5$), and Reactive ($0.3, 0.8, 0.7$). Profiles are fixed per run but vary across runs. The use of trait-based behavioral modulation draws on knowledge-engineering perspectives that integrate symbolic traits with subsymbolic inference [23].

Behavioral traits modify inference through three mechanisms:

1. Membership Scaling:

$$\mu'_A(x) = \mu_A(x + \delta_{RA} \cdot (RA_n - 0.5)) \quad (10)$$

with $\delta_{RA} = 0.2$. High-RA agents shift "Low" inventory membership leftward, triggering earlier orders.

2. Rule Weight Modulation:

$$w'_i = w_i \cdot (1 + \gamma_{AD} \cdot (AD_n - 0.5) \cdot \mathbb{I}_{\text{adaptive}}(i) + \gamma_{IP} \cdot (IP_n - 0.5) \cdot \mathbb{I}_{\text{external}}(i)) \quad (11)$$

with $\gamma_{AD} = \gamma_{IP} = 0.3$.

3. Output Biasing:

$$u'_{n,t} = u_{n,t} + \beta_{RA} \cdot (RA_n - 0.5) \quad (12)$$

with $\beta_{RA} = 0.1$, clipped to $[0, 1]$.

5.2 Agent Design and Fuzzy Inference Pipeline

Each agent contains a behavior module that personalizes the fuzzy controller by adjusting rule weights or fuzzification boundaries. Figure 2 shows the internal structure. This modular architecture aligns with design principles for fuzzy controllers that separate inference from tuning parameters [8].

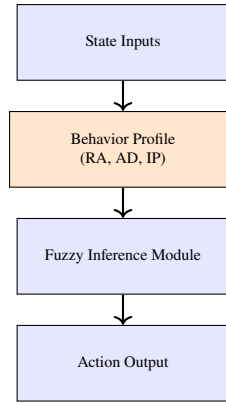


Figure 2: Architecture of a fuzzy decision agent with integrated behavioral profile.

Figure 3 illustrates the complete decision flow, where behavioral traits dynamically adjust fuzzification and rule prioritization.

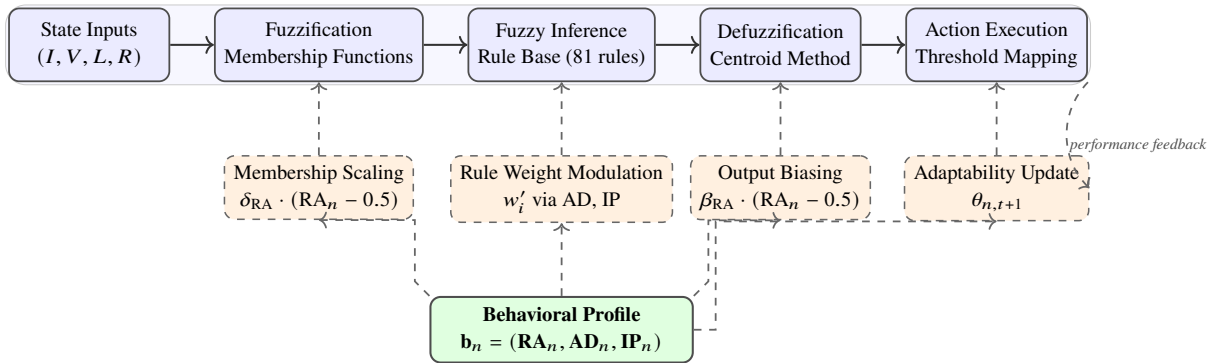


Figure 3: Complete fuzzy decision flow with behavioral modulation. Solid arrows indicate the main processing pipeline; dashed arrows indicate behavioral modulation pathways. The behavioral profile $\mathbf{b}_n$ influences membership scaling, rule weight modulation, output biasing, and threshold adaptation.

5.3 Modifying Inference with Behavior

Behavior profiles influence membership scaling, rule weights, and output biasing. Highly adaptive agents adjust decision thresholds dynamically.

5.3.1 Adaptability Update Mechanism

Let $\theta_{n,t}$ be the action threshold, initialized to $\theta_{n,0} = 0.5$. At each step, the agent observes performance signal $p_{n,t} \in [0, 1]$:

$$p_{n,t} = \left| \frac{D_{n,t} - \hat{D}_{n,t}}{\hat{D}_{n,t}} \right|, \quad \text{clipped to } [0, 1] \quad (13)$$

The threshold updates via:

$$\theta_{n,t+1} = \theta_{n,t} + \eta \cdot \text{AD}_n \cdot (p_{n,t} - \theta_{n,t}) \quad (14)$$

with $\eta = 0.1$. The updated threshold modulates action mapping:

$$\text{Action}_{n,t} = \begin{cases} \text{Defer} & u'_{n,t} < \theta_{n,t} - 0.2 \\ \text{Normal Order} & \theta_{n,t} - 0.2 \leq u'_{n,t} \leq \theta_{n,t} + 0.1 \\ \text{Expedited Order} & u'_{n,t} > \theta_{n,t} + 0.1 \end{cases} \quad (15)$$

Algorithm 1 summarizes this mechanism. The use of performance-signal-driven threshold adaptation reflects principles from adaptive control and fuzzy systems design [9].

Algorithm 1 Adaptability Update Mechanism

0: **Input:** Agent n , time t , demand $D_{n,t}$, forecast $\hat{D}_{n,t}$, threshold $\theta_{n,t}$, trait AD_n
0: **Output:** Updated threshold $\theta_{n,t+1}$, action $\text{Action}_{n,t}$
0: Compute performance signal: $p_{n,t} \leftarrow \min\left(\left|\frac{D_{n,t} - \hat{D}_{n,t}}{\hat{D}_{n,t}}\right|, 1\right)$
0: Update threshold: $\theta_{n,t+1} \leftarrow \theta_{n,t} + 0.1 \cdot \text{AD}_n \cdot (p_{n,t} - \theta_{n,t})$
0: Compute urgency score $u'_{n,t}$ via fuzzy inference (Eq. (12))
0: Map to action using Eq. (15)
0: **return** $\theta_{n,t+1}$, $\text{Action}_{n,t} = 0$

5.3.2 Complete Decision Pipeline Algorithm

Algorithm 2 describes the complete pipeline from state observation through fuzzification, behavioral modulation, inference, defuzzification, and action execution.

Algorithm 2 Complete Fuzzy Behavioral Decision Pipeline

0: **Input:** Agent n , time t , state $\mathbf{x}_{n,t} = (I_{n,t}, V_{n,t}, L_{n,t}, R_{n,t})$, behavioral profile $\mathbf{b}_n = (\text{RA}_n, \text{AD}_n, \text{IP}_n)$, threshold $\theta_{n,t}$
0: **Output:** Action $\text{Action}_{n,t}$, updated threshold $\theta_{n,t+1}$
0: **Step 1: Fuzzification**
0: **for** each input variable $x \in \mathbf{x}_{n,t}$ **do**
0: Compute membership degrees $\mu_A(x)$ for all linguistic terms A
0: Apply behavioral membership scaling: $\mu'_A(x) \leftarrow \mu_A(x + \delta_{\text{RA}} \cdot (\text{RA}_n - 0.5))$ {Eq. (10)}
0: **end for**
0: **Step 2: Behavioral Rule Weight Modulation**
0: **for** each rule $i = 1, \dots, 81$ **do**
0: Compute modulated weight w'_i using Eq. (11)
0: **end for**
0: **Step 3: Fuzzy Inference**
0: **for** each rule $i = 1, \dots, 81$ **do**
0: Compute firing strength $\alpha_i \leftarrow \min(\mu'_{A_{i1}}, \mu'_{A_{i2}}, \mu'_{A_{i3}}, \mu'_{A_{i4}}) \cdot w'_i$ {Eq. (16)}
0: **end for**
0: Aggregate output: $\mu_B(y) \leftarrow \max_{i=1}^{81} \min(\alpha_i, \mu_{B_i}(y))$ {Eq. (17)}
0: **Step 4: Defuzzification**
0: Compute crisp urgency: $u_{n,t} \leftarrow \frac{\int y \cdot \mu_B(y) dy}{\int \mu_B(y) dy}$ {Centroid method}
0: Apply behavioral output bias: $u'_{n,t} \leftarrow \text{clip}(u_{n,t} + \beta_{\text{RA}} \cdot (\text{RA}_n - 0.5), 0, 1)$ {Eq. (12)}
0: **Step 5: Action Execution**
0: Map urgency to action using adaptive thresholds: $\text{Action}_{n,t} \leftarrow \text{MapAction}(u'_{n,t}, \theta_{n,t})$ {Eq. (15)}
0: **Step 6: Adaptability Update**
0: Compute performance signal: $p_{n,t} \leftarrow \min(|D_{n,t} - \hat{D}_{n,t}| / \hat{D}_{n,t}, 1)$
0: Update threshold: $\theta_{n,t+1} \leftarrow \theta_{n,t} + 0.1 \cdot \text{AD}_n \cdot (p_{n,t} - \theta_{n,t})$ {Eq. (14)}
0: **return** $\text{Action}_{n,t}$, $\theta_{n,t+1} = 0$

This modular framework supports integration of psychological or operational traits, enabling simulations that explore decision dynamics under varied human-like conditions. The behavioral traits RA, AD, and IP are simulated heuristics, not calibrated against empirical data; “human-like” describes qualitative resemblance to documented biases, not empirical fidelity. Calibration against field data is future work (Section 7).

6. Rule Generation and Action Mapping

The rule base maps input conditions to output actions via if-then statements. A typical rule is: IF *Inventory* is Low AND *Demand Volatility* is High THEN *Urgency* is High. Linguistic modifiers correspond to fuzzy sets; the output is defuzzified to an action scalar.

6.1 Rule Base Construction

Rules are generated via manual encoding (expert-defined best practices), combinatorial enumeration (all term combinations, feasible rules retained), and behavioral filters (traits deactivate or modify conflicting rules). Each rule has weight $w_i \in [0, 1]$. In reported experiments, weights were manually defined by domain experts (Table 5); no automated training or tuning was performed. Behavioral modulation of weights is a deterministic function of traits and does not constitute learning. Automated tuning via reinforcement learning or evolutionary optimization is future work (Section 7). The manual curation approach follows established practice in fuzzy controller design [8].

6.1.1 Complete Fuzzy Rule Base

The base has $3 \times 3 \times 3 \times 3 = 81$ rules covering *Inventory* (Low, Medium, High), *Demand Volatility* (Low, Medium, High), *Delivery Delay* (Short, Moderate, Long), and *Risk Perception* (Low, Medium, High), mapping to *Urgency* (Low, Medium, High). Table 5 defines the base.

Table 5: Complete fuzzy rule base. Rows: Inventory (Inv), Demand Volatility (Vol), Delivery Delay (Del), Risk Perception (Risk). Output: Urgency (Urg). Weights w are shown in parentheses.

Antecedents				Consequent: Urgency							
Inv	Vol	Del	Risk	Urg	w	Inv	Vol	Del	Risk	Urg	w
L	L	S	L	M	0.8	M	L	S	L	L	0.7
L	L	S	M	M	0.9	M	L	S	M	M	0.8
L	L	S	H	H	0.9	M	L	S	H	M	0.9
L	L	M	L	M	0.8	M	L	M	L	L	0.7
L	L	M	M	H	0.8	M	L	M	M	M	0.8
L	L	M	H	H	0.9	M	L	M	H	H	0.8
L	L	L	L	H	0.9	M	L	L	L	M	0.8
L	L	L	M	H	0.9	M	L	L	M	M	0.9
L	L	L	H	H	1.0	M	L	L	H	H	0.9
L	M	S	L	M	0.8	M	M	S	L	M	0.8
L	M	S	M	H	0.9	M	M	S	M	M	0.9
L	M	S	H	H	0.9	M	M	S	H	H	0.9
L	M	M	L	H	0.8	M	M	M	L	M	0.8
L	M	M	M	H	0.9	M	M	M	M	H	0.8
L	M	M	H	H	1.0	M	M	M	H	H	0.9
L	M	L	L	H	0.9	M	M	L	L	H	0.8
L	M	L	M	H	1.0	M	M	L	M	H	0.9
L	M	L	H	H	1.0	M	M	L	H	H	1.0
L	H	S	L	H	0.9	M	H	S	L	M	0.8
L	H	S	M	H	1.0	M	H	S	M	H	0.9
L	H	S	H	H	1.0	M	H	S	H	H	1.0
L	H	M	L	H	0.9	M	H	M	L	H	0.8
L	H	M	M	H	1.0	M	H	M	M	H	0.9
L	H	M	H	H	1.0	M	H	M	H	H	1.0
L	H	L	L	H	1.0	M	H	L	L	H	0.9
L	H	L	M	H	1.0	M	H	L	M	H	1.0
L	H	L	H	H	1.0	M	H	L	H	H	1.0
H	L	S	L	L	0.7	H	M	S	L	L	0.7
H	L	S	M	L	0.8	H	M	S	M	L	0.7
H	L	S	H	M	0.8	H	M	S	H	M	0.8
H	L	M	L	L	0.7	H	M	M	L	L	0.7
H	L	M	M	L	0.7	H	M	M	M	L	0.7
H	L	M	H	M	0.8	H	M	M	H	M	0.8
H	L	L	L	M	0.8	H	M	L	L	L	0.7
H	L	L	M	M	0.8	H	M	L	M	M	0.8
H	L	L	H	M	0.9	H	M	L	H	M	0.9
H	H	S	L	M	0.8	H	H	S	L	M	0.8
H	H	S	M	M	0.9	H	H	S	M	M	0.9
H	H	S	H	H	0.9	H	H	S	H	H	0.9
H	H	M	L	M	0.8	H	H	M	L	M	0.8
H	H	M	M	M	0.9	H	H	M	M	H	0.9
H	H	M	H	H	0.9	H	H	M	H	H	1.0
H	H	L	L	H	0.9	H	H	L	L	M	0.8
H	H	L	M	H	0.9	H	H	L	M	H	0.9
H	H	L	H	H	1.0	H	H	L	H	H	1.0

Weights $w \in [0, 1]$ are confidence values assigned during manual curation and behavioral tuning. Firing strength of rule i :

$$\alpha_i = \min(\mu_{A_{i1}}(x_1), \mu_{A_{i2}}(x_2), \mu_{A_{i3}}(x_3), \mu_{A_{i4}}(x_4)) \cdot w_i \quad (16)$$

Aggregated output:

$$\mu_B(y) = \max_{i=1}^{81} \min(\alpha_i, \mu_{B_i}(y)) \quad (17)$$

This min-max aggregation follows the inference pattern established by Mamdani for fuzzy control applications [4].

6.2 Rule Prioritization with Behavior Profiles

Traits RA and IP scale rule weights before inference: high RA increases weights for early-ordering rules under uncertainty; low IP reduces influence of peer-driven rules. The same rule base thus produces different outcomes across agents. This approach to trait-modulated rule weighting is conceptually related to knowledge-engineering frameworks that separate symbolic rule structure from subsymbolic parameter adjustment [23].

6.3 Output Mapping and Action Execution

The defuzzified urgency score maps to discrete actions via piecewise thresholds:

- **Score** < 0.3: No action (Defer)
- **Score** 0.3–0.6: Normal order
- **Score** > 0.6: Expedited order

Thresholds $\tau_1 = 0.3$ and $\tau_2 = 0.6$ balance operational concerns: the interval $[0.3, 0.6]$ aligns with the "Medium" urgency membership function; the lower threshold avoids excessive deferral (stockouts), and the upper threshold controls expediting costs. Sensitivity analysis (Table 6) confirms this choice. Similar threshold-based action mapping is common in fuzzy control systems where defuzzified outputs must be converted to discrete actuator commands [9].

Table 6: Sensitivity analysis of action thresholds τ_1 and τ_2 for the HV-HD scenario (mean over 30 runs).

τ_1	τ_2	Stockout Rate	Expediting Frequency
0.2	0.5	0.251	0.312
0.2	0.6	0.248	0.287
0.2	0.7	0.246	0.265
0.3	0.5	0.273	0.298
0.3	0.6	0.267	0.274
0.3	0.7	0.271	0.251
0.4	0.5	0.289	0.276
0.4	0.6	0.285	0.258
0.4	0.7	0.282	0.239

Future extensions could include reinforcement learning to adjust rule weights, evolutionary optimization to evolve rule sets, and data-driven synthesis from historical datasets. Rule generation and action mapping form the operational core of the fuzzy behavioral agents, enabling flexible, explainable, and customizable decision logic for adaptive supply chain analytics.

7. Conclusion and Future Applications

This paper has presented a fuzzy behavioral AI framework for adaptive, interpretable decision-making in supply chain systems. The approach is methodologically grounded and demonstrates, within a simulated supply chain environment, how fuzzy logic can enable agents to exhibit context-aware behaviors. The reported experiments show that behaviorally guided logic reduces stockout rates, shortens lead times, and improves responsiveness relative to a static rule-based baseline under the tested scenarios. These

improvements are specific to the simulation configurations described in Section 3 and 3.3; generalization to real-world supply chains requires further validation [21].

The system architecture supports modular fuzzy controllers at each node of the supply chain, incorporating real-time state inputs and qualitative traits like risk aversion, adaptability, and information preference. This integration enables diverse decision styles across agents, allowing researchers and practitioners to simulate and analyze a wide spectrum of operational behaviors. Such modular, interpretable designs align with broader trends toward explainable and human-aligned AI in operational systems.

We detailed the underlying fuzzy logic mechanisms: membership functions, rule bases, inference, and defuzzification, as well as the influence of behavioral traits on rule prioritization and output mapping. Our methodology offers a transparent and flexible platform that balances computational decision-making with human-like adaptability. This balance is increasingly important as supply chains adopt AI-driven automation at scale [2].

7.1 Key Contributions

The major contributions of our work are as follows:

- A novel hybrid framework that integrates fuzzy logic with behavioral traits for supply chain decision agents.
- A simulation environment with adjustable volatility, delays, and behavioral configurations for scenario testing.
- Mechanisms for dynamically prioritizing fuzzy rules based on agent personality profiles.
- Modular action mapping strategies that convert fuzzy outputs into real-world logistics decisions.

7.2 Future Work

Several promising directions emerge from this research:

- **Real-World Integration:** Deploy the framework in digital twin systems for real-time logistics operations, enabling behavior-aware automation [22].
- **Behavioral Cloning:** Learn rule profiles from actual human operator data using inverse reinforcement learning or supervised behavioral cloning.
- **Hybrid AI Models:** Integrate fuzzy logic with reinforcement learning to allow adaptive rule tuning based on performance feedback.
- **Explainable AI (XAI):** Further enhance the interpretability of agent decisions using visual and textual explanations derived from fuzzy trace reasoning [17].
- **Field Validation:** Conduct real-world case studies to validate the practical effectiveness and operational relevance of the proposed fuzzy behavioral framework in diverse supply chain contexts.

7.2.1 Distinction Between Current Contributions and Future Extensions

To avoid ambiguity, we explicitly distinguish the capabilities implemented and evaluated in this paper from the proposed future extensions:

- **Implemented and Evaluated:** (i) Modular fuzzy inference system with triangular/trapezoidal membership functions; (ii) Behavioral modulation of membership functions, rule weights, and output bias; (iii) Adaptive threshold update mechanism; (iv) Action mapping via urgency thresholds; (v) Simulation environment with stochastic demand and delays; (vi) Comparative evaluation against a static rule-based baseline with statistical validation.
- **Proposed Future Extensions (Not Implemented):** (i) Digital-twin integration for real-time logistics; (ii) Behavioral cloning from human operator data; (iii) Reinforcement-learning-based rule tuning; (iv) Real-world field validation; (v) Evolutionary optimization of rule sets; (vi) Data-driven fuzzy rule synthesis from historical datasets [20].

All claims in Sections 3–6 refer to implemented capabilities. Claims in Section 7 clearly label proposed extensions as future work.

7.3 Final Remarks

As supply chains become more complex and dynamic, the demand for AI systems that are not only intelligent but also interpretable and human-aligned continues to grow. Fuzzy behavioral models provide a viable pathway for bridging the gap between rigid optimization and flexible, human-like reasoning. Our framework lays the groundwork for future supply chain decision systems that are adaptive, explainable, and potentially operationally robust, pending further validation in real-world settings.

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