Type-2 Fuzzy Monte Carlo Model for Supply Chain Resilience under Uncertainty

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This study presents a Type-2 Fuzzy Monte Carlo framework using PERT distributions to quantify supply-chain resilience under deep uncertainty. The approach integrates linguistic ambiguity (via interval Type-2 fuzzy sets) with stochastic variability (via PERT-based sampling) to capture both epistemic and aleatory uncertainty. Applied to an electric-vehicle supply chain, the model estimates resilience indices and confidence bounds through iterative simulation. Results show that flexibility and visibility interactions critically shape resilience outcomes, offering managerial insights on investment priorities and risk-adjusted robustness. The framework advances quantitative modeling of resilience where probability data and expert judgments coexist.

Keywords: Supply Chain Resilience, Type-2 Fuzzy Logic, Deep Uncertainty, Monte Carlo Simulation.

1. Introduction

The rising number and scale of global disruptions have shaken the stability of supply chains across almost every industry. Events like the COVID-19 pandemic, semiconductor shortages, geopolitical tensions, and climate-driven disturbances have shown how fragile even the most advanced manufacturing networks can be (Ivanov, 2021; Sheffi, 2005). This is especially true for high-tech sectors—electric vehicles (EVs) and electronics, for instance—where systems are tightly interconnected, supplier relationships are complex, and components can become scarce overnight. Such shocks don't just interrupt production; they also push firms to rethink how they plan for resilience, making it essential to measure and manage uncertainty across the entire value chain (Christopher & Peck, 2004).

Traditionally, SCR measurement has leaned on deterministic or probabilistic models. Deterministic approaches assume that disruption and recovery follow predictable patterns, while probabilistic ones—like stochastic optimization or Monte Carlo methods—try to capture randomness but still depend on well-defined probability distributions (Rajesh, 2020). In reality, though, many of the factors that influence resilience—flexibility, visibility, collaboration, redundancy—are based on expert opinion or vague linguistic assessments instead of hard data. These subjective judgments bring in epistemic uncertainty, which comes from incomplete, imprecise, or ambiguous information (Walker et al., 2013). Standard stochastic tools or even Type-1 fuzzy models struggle here because they cannot fully represent the extra layer of uncertainty that comes from experts disagreeing or changing their views over time (Mendel & John, 2002).

To deal with this, resilience modeling under deep uncertainty needs hybrid methods that can capture both epistemic uncertainty (vagueness, linguistic ambiguity) and aleatory uncertainty (natural randomness). Combining Type-2 fuzzy logic with Monte Carlo simulation offers a practical way forward. Type-2 fuzzy sets use their Footprint of Uncertainty (FOU) to express uncertainty inside membership functions, which helps interpret expert linguistic inputs more flexibly (Zadeh, 1965; Mendel & John, 2002). At the same time, Monte Carlo simulation with PERT (Program Evaluation and Review Technique) distributions captures bounded randomness using optimistic, most-likely, and pessimistic estimates—something managers are often comfortable providing (Moder & Rogers, 1968; Metropolis & Ulam, 1949).

This paper therefore focuses on one central question:

How can Type-2 fuzzy logic, combined with PERT-based Monte Carlo simulation, be used to quantify supply-chain resilience under uncertainty?

To address this, a hybrid modeling framework—the Type-2 Fuzzy Monte Carlo (T2F-MC) model—is developed. The framework (i) builds a mathematical approach for computing a resilience index under dual uncertainty, (ii) merges linguistic and numerical inputs in a single simulation environment, and (iii) illustrates its use through a case study of a high-tech manufacturing supply chain in the EV and electronics domain. The model produces both a numerical resilience value and a fuzzy-stochastic confidence interval, helping managers understand not just "how resilient" the supply chain is, but also "how confident" they should be in that assessment.

2. Literature Review

2.1 Supply Chain Resilience (SCR)

Supply Chain Resilience (SCR) has become a vital capability for companies trying to operate in today's increasingly unpredictable world. At its core, SCR refers to how well a supply chain can prepare for disruptions, respond when they happen, and eventually recover—while still keeping performance at an acceptable level (Ponomarov & Holcomb, 2009).

Christopher and Peck (2004) explain that a resilient supply chain doesn't just react; it anticipates trouble through smart design, flexibility, and shared risk management. Sheffi (2005) adds that resilience is both a structural and cultural trait that helps firms "bounce back" from disruptions faster than their rivals.

Resilience is commonly viewed as unfolding across four connected phases—readiness, response, recovery, and adaptation (Ivanov, 2021).

- The readiness phase focuses on preparation, redundancy, and scenario planning done upfront.
- The response phase deals with the immediate actions taken once a disruption strikes.
- The recovery phase works toward bringing operations back to acceptable functioning levels.
- The adaptation phase emphasizes learning and redesigning strategies to strengthen resilience going forward.

A wide look at SCR metrics highlights several well-known resilience enablers:

- Flexibility: being able to shift suppliers or production quickly.
- Visibility: gaining real-time insight into material and information flows.
- Collaboration: coordinating and communicating effectively across partners.
- Redundancy: using spare capacity, safety stock, or multi-sourcing.
- Recovery speed: how fast operations return to normal after disruptions.

Together, these factors influence the composite resilience index often used in quantitative studies (Rajesh, 2020). But most of these enablers are judged qualitatively rather than measured directly, which naturally introduces ambiguity in the inputs—something this study places at the centre of discussion.

2.2 Modeling Approaches for Resilience

Modeling SCR is challenging because it requires juggling different data types, sources of uncertainty, and decision criteria. Over time, researchers have settled on three main quantitative approaches: probabilistic models, fuzzy methods, and hybrid simulation-based frameworks. Probabilistic models—like stochastic programming, scenario analysis, and Monte Carlo simulation—capture randomness in things such as demand, lead times, or failure probabilities. Monte Carlo methods, first proposed by Metropolis and Ulam (1949), simulate system behavior by repeatedly sampling from uncertain variables. Later supply-chain studies used these techniques to explore disruption scenarios and evaluate trade-offs in cost or service performance (Sawik, 2022). While effective at handling randomness, these models assume that probability distributions are well defined, which is often not the case when data are limited or messy.

Fuzzy logic approaches help fill this gap by incorporating linguistic or subjective descriptions. Rooted in Zadeh's (1965) fuzzy set theory, these models translate uncertain concepts—like "high flexibility" or "moderate visibility"—into membership functions instead of fixed numbers. Type-1 fuzzy systems have been widely applied in supply-chain decisions, especially in methods such as Fuzzy AHP, Fuzzy TOPSIS, and Fuzzy DEMATEL (Rajesh, 2020). These techniques blend expert opinions to produce weighted resilience scores. However, Type-1 fuzzy sets still assume that membership levels are exact, which means they cannot truly capture disagreements between experts or evolving interpretations over time.

To address these issues, researchers have developed hybrid and simulation-based models that merge fuzzy logic with probabilistic sampling. For example, Gunessee and Subramanian (2020) integrated fuzzy risk assessments with simulation to study recovery strategies when information is ambiguous. Although such methods add realism, they continue to rely on Type-1 fuzzy structures, which do not account for uncertainty within the membership function itself. As a result, existing models tend to handle either randomness (aleatory uncertainty) or imprecision (epistemic uncertainty), but rarely both at the same time.

2.3 Deep Uncertainty and Hybrid Approaches

In real-world situations—especially in high-tech manufacturing—uncertainty extends far beyond simple randomness or measurement noise. It reaches into what Lempert, Popper, and Bankes (2003) call deep uncertainty. This type of uncertainty appears when decision-makers either don't know or cannot agree on (i) how the system really works, (ii) which probability distributions describe key variables, or (iii) how much weight different outcomes should carry. In these cases, traditional probabilistic models that rely on a single "correct" distribution fall short. Recent studies have tried to close the gap between expert experience and quantitative evidence by using hybrid fuzzy–stochastic methods. These approaches pair fuzzy logic (to capture epistemic vagueness) with random simulation (to account for aleatory variability). For example, Yoon and Park (2019) proposed a fuzzy–stochastic model that used Beta distributions to capture cost uncertainty and fuzzy sets to assess supplier reliability. Likewise, Zhao et al. (2021) explored fuzzy random variables to handle dual uncertainty in logistics networks. Still, most of the existing work sticks to Type-1 fuzzy sets and standard distribution shapes like normal or triangular, which limits how well they can express uncertainty in both the shape and confidence of the membership functions.

The Interval Type-2 Fuzzy Set (IT2FS) concept introduced by Mendel and John (2002) builds on Type-1 fuzziness by allowing the membership function itself to vary within upper and lower bounds, forming a Footprint of Uncertainty (FOU). This extra flexibility helps capture differences in expert opinions or shifts in perception over time—both common in fast-changing manufacturing environments. When such fuzzy structures are combined with stochastic simulation, the result is a dual-layer uncertainty analysis where epistemic and aleatory uncertainties interact rather than being treated separately.

2.4 Research Gap and Novelty

The review makes one gap very clear. Although Monte Carlo methods and fuzzy systems have each been used for resilience assessment, there is no existing model that blends Interval Type-2 fuzzy inference with PERT-based random sampling to produce a quantitative resilience index. PERT (Program Evaluation and Review Technique) distributions are especially suitable because they capture optimistic, most-likely, and pessimistic estimates in a bounded and slightly asymmetric form, which aligns well with how managers usually think about uncertainty (Moder & Rogers, 1968).

The novelty of this study can be summarized as:

1. Introducing a Type-2 Fuzzy Monte Carlo (T2F-MC) model that merges IT2FS with PERT-driven stochastic sampling.
2. Measuring resilience under deep uncertainty by including both linguistic ambiguity and random variation.
3. Delivering a reproducible computational setup that generates a resilience index along with confidence bounds.

By tackling both epistemic and aleatory uncertainty together, the proposed model strengthens the quantitative foundations of resilience analytics for high-tech manufacturing supply chains.

3. Methodology

3.1 Overview of the Framework

This research develops a quantitative framework called the Type-2 Fuzzy Monte Carlo (T2F-MC) model to evaluate supply-chain resilience (SCR) under dual uncertainty. The methodology integrates (i) interval Type-2 fuzzy logic for modeling *epistemic* (linguistic or subjective) uncertainty and (ii) Monte Carlo simulation using PERT (Program Evaluation and Review Technique) distributions for *aleatory* (stochastic) variability.

The overall architecture comprises four layers (conceptually illustrated in Fig. 1):

1. Input Layer – Data and Expert Elicitation Identify key resilience factors $F = \{\text{Flexibility,Visibility,Collaboration,Redundancy,Recovery Speed}\}$. For each factor f:

- Collect linguistic rating $\mathcal{L}_f \in \{\text{Low,Medium,High}\}$;
- Obtain PERT parameters (a_f, m_f, b_f) = (pessimistic, most-likely, optimistic);
- Assign importance weight w_f such that $\sum_f w_f = 1$.

2. Type-2 Fuzzy Layer – Epistemic Uncertainty Representation Convert each $\mathcal{L}_f$ to an Interval Type-2 Fuzzy Set (IT2FS) defined by upper and lower Gaussian membership functions, capturing disagreement or imprecision in expert opinions.
3. Monte Carlo + PERT Layer – Aleatory Uncertainty Propagation for each iteration i, generate random samples $X_f^{(i)}$ from the PERT distribution to represent stochastic variation in each resilience factor.
4. Output Layer – Resilience Index Computation For each simulation, evaluate fuzzy memberships, defuzzify to crisp scores, and aggregate to compute the overall resilience index$R^{(i)}$. Summarize results as a probability–fuzzy distribution with mean, variance, and confidence intervals.

This layered integration enables the model to quantify both *"how resilient"* and *"how certain"* the supply chain is.

3.2 Mathematical Formulation

Step 1: Input Definition

Each factor f $(1 \le f \le F)$ is characterized by

$$a_f = \text{pessimistic value}, \qquad m_f = \text{most-likely value}, \qquad b_f = \text{optimistic value}, \qquad w_f = \text{factor weight}, \quad \sum_f w_f = 1.$$

The linguistic evaluation $\mathcal{L}_f$ is mapped to lower and upper Gaussian membership functions forming the Footprint of Uncertainty (FOU)

$$\underline{\mu}_{\mathcal{L}_f}(x) = \exp\left[-\frac{(x-\mu_\ell)^2}{2\sigma_\ell^2}\right], \qquad \overline{\mu}_{\mathcal{L}_f}(x) = \exp\left[-\frac{(x-\mu_u)^2}{2\sigma_u^2}\right],$$

Where $\underline{\mu}$ and $\overline{\mu}$ represent lower and upper membership grades.

Step 2: PERT-Based Sampling

PERT distributions model bounded random variability. Their equivalent Beta parameters are

$$\alpha_f = 1 + 4\frac{m_f - a_f}{b_f - a_f}, \qquad \beta_f = 1 + 4\frac{b_f - m_f}{b_f - a_f}.$$

For iteration$i$, draw

$$X_f^{(i)} = a_f + (b_f - a_f)\, B(\alpha_f, \beta_f),$$

Where $B(\alpha, \beta)$ is a Beta-distributed variable on[0,1], so $X_f^{(i)} \in [a_f, b_f]$.

Step 3: Interval Type-2 Membership Evaluation
For the sampled$X_f^{(i)}$, compute

$$\underline{\mu}_f^{(i)} = \underline{\mu}_{\mathcal{L}_f}(X_f^{(i)}), \qquad \overline{\mu}_f^{(i)} = \overline{\mu}_{\mathcal{L}_f}(X_f^{(i)}).$$

These define the membership interval $[\underline{\mu}_f^{(i)}, \overline{\mu}_f^{(i)}]$; its width $\overline{\mu}_f - \underline{\mu}_f$ reflects epistemic uncertainty.

Step 4: Type-Reduction and Defuzzification
The classical Karnik–Mendel (KM) procedure yields the centroid interval $[y_L, y_R]$ of an IT2FS

$$y_L = \frac{\sum_f c_f \, \mu_f^{\downarrow}}{\sum_f \mu_f^{\downarrow}}, \qquad y_R = \frac{\sum_f c_f \, \mu_f^{\uparrow}}{\sum_f \mu_f^{\uparrow}},$$

Where c_f are consequent values (the sampled $X_f^{(i)}$) and $\mu_f^{\downarrow}, \mu_f^{\uparrow} \in \{\underline{\mu}_f^{(i)}, \overline{\mu}_f^{(i)}\}$.
For Monte Carlo efficiency, a centroid approximation is used:

$$s_f^{(i)} = 1/2\left(\underline{\mu}_f^{(i)} + \overline{\mu}_f^{(i)}\right),$$

Yielding a single crisp score $s_f^{(i)}$ for each factor per iteration.
Step 5: Aggregation into Resilience Index
The iteration-level resilience index is

$$R^{(i)} = \sum_{f=1}^{F} w_f \; s_f^{(i)}.$$

After N iterations,

$$\bar{R} = \frac{1}{N}\sum_{i=1}^{N} R^{(i)}, \qquad \sigma_R = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N} (R^{(i)} - \bar{R})^2}.$$

A 95% confidence interval for resilience is

$$[\bar{R} - 1.96\,\sigma_R, \; \bar{R} + 1.96\,\sigma_R],$$

Producing a fuzzy–probabilistic distribution rather than a single value.

3.3 Sensitivity and Robustness Analysis

To test robustness, perturb either the most-likely value m_f or the membership-function width $(\sigma_u - \sigma_\ell)$ by $\pm 10\%$. For each perturbation$p$, run the simulation and compute $\bar{R}_p$. The sensitivity coefficient is

$$S_f = \frac{\bar{R}_{+10\%} - \bar{R}_{-10\%}}{\bar{R}_{\text{base}}}.$$

A larger S_f denotes higher impact, indicating priority areas for managerial attention.

3.4 Implementation Environment

The T2F-MC framework is implemented in Python 3.12 using NumPy, Pandas, and Matplotlib. Inputs and outputs are handled through Excel to facilitate managerial use. Typical runs with $N = 5000–10000$ iterations ensure stable convergence.

4. Case Study: High-Tech Manufacturing Supply Chain

4.1 Context and Background

To demonstrate how the proposed Type-2 Fuzzy Monte Carlo (T2F-MC) model works in practice, a representative case study was carried out on a high-tech manufacturing supply chain that blends both electric-vehicle (EV) and electronics components. This industry is known for its intricate products, unpredictable demand swings, and supplier networks scattered across different regions. Recent disruptions—ranging from semiconductor shortages to shipping bottlenecks and geopolitical trade limitations—have exposed just how fragile these supply chains can be.

The company examined here is an original equipment manufacturer (OEM) producing battery modules, power converters, and electronic control units for EVs and advanced electronics. It relies on global suppliers for critical materials such as lithium, semiconductors, sensors, and printed-circuit assemblies. Since many of these components are scarce and highly specialized, even a small disturbance in the supply base can ripple through the production system, delaying manufacturing schedules and affecting delivery commitments.

4.2 Selection of Resilience Factors

Following the literature, five core resilience enablers were identified:

Resilience Factors and Managerial Interpretation

Factor	Description	Managerial Interpretation
Supplier Flexibility	Ability to switch or add suppliers when disruptions occur.	Measured through supplier adaptability and reconfiguration speed.
Visibility	Extent of real-time information sharing across the supply network.	Captures transparency, digital tracking, and control-tower capability.
Collaboration	Degree of cooperative behavior among partners during disruption.	Reflects information exchange and joint recovery planning.
Redundancy	Availability of spare capacity, backup suppliers, or safety inventory.	Represents intentional buffers and dual-sourcing strategies.
Recovery Speed	Time required to return to target performance post-disruption.	Expressed as a normalized recovery-time index.

Each factor was assessed using a linguistic scale (*Low, Medium, High*) to reflect managerial perceptions, while quantitative uncertainty was expressed through PERT parameters derived from expert workshops.

4.3 Input Data and Structure

The following input Parameters for the T2F-MC Model are used.

Factor	Linguistic Term	a (Pessimistic)	m (Most-Likely)	b (Optimistic)
Supplier Flexibility	High	0.55	0.75	0.90
Visibility	Medium	0.40	0.60	0.80
Collaboration	High	0.50	0.70	0.85
Redundancy	Medium	0.35	0.55	0.75
Recovery Speed	High	0.6	0.70	0.90

The linguistic terms were converted into interval Type-2 fuzzy membership functions using Gaussian parameters drawn from calibration studies (Table 1).

Linguistic Scale Calibration for Interval Type-2 Fuzzy Sets

Term	μ_ℓ	μ_u	σ_ℓ	σ_u
Low	0.20	0.30	0.10	0.12
Medium	0.50	0.60	0.10	0.12
High	0.70	0.85	0.08	0.10

Each linguistic category thus has a Footprint of Uncertainty (FOU) bounded by the lower and upper Gaussian curves, representing epistemic vagueness in expert perception.

4.4 Simulation Setup

The model was implemented in Python using NumPy for random sampling and Matplotlib for visualization. A total of $N = 3000$ Monte Carlo iterations were performed for convergence stability.

5. Results and Discussion

5.1 Simulation Outcomes

The Monte Carlo simulation generated a distribution of resilience indices across 3,000 iterations. The mean resilience index was $\bar{R} = 0.648$ with a standard deviation $\sigma_R = 0.065$. Figure 1 illustrates the probability density of the simulated resilience index and Figure 2 illustrates factor-wise contribution.

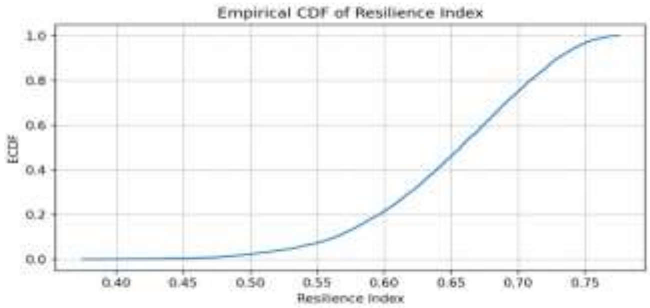

Figure 1 *Probability density of the resilience index*

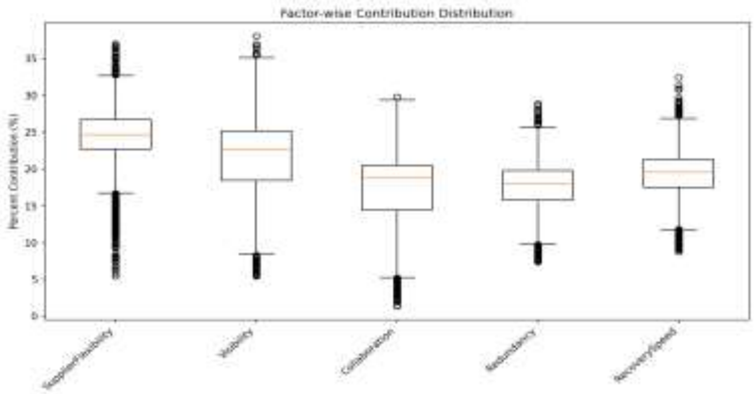

Figure 2 *Factor-Wise Contribution Distribution*

Monte Carlo Distribution of the Resilience Index

The distribution reveals moderate right skewness, indicating that while most scenarios yield average resilience, a few high-performing configurations (typically with higher flexibility and visibility) achieve superior outcomes. This behavior aligns with the expected nonlinear effects of redundancy and recovery speed in complex supply chains.

Factor Contributions and Sensitivity

The contribution of each resilience factor was analyzed by decomposing its weighted average across all iterations. Table 1 presents the normalized contribution scores.

Table 1 *Contribution of Factors to Overall Resilience*

Factor	Mean Contribution (%)	Sensitivity Coefficient (S_f)
Supplier Flexibility	24.3	0.155
Visibility	21.6	-0.24
Collaboration	17.0	0.335
Redundancy	17.7	0.009
Recovery Speed	19.3	0.196

Supplier Flexibility and Visibility collectively accounted for more than 45% of the overall resilience effect, reinforcing their strategic significance in dynamic and volatile environments. Redundancy showed diminishing marginal returns, confirming that over-buffering may not proportionally enhance resilience.

The sensitivity analysis revealed that a 10% increase in the most-likely PERT parameter m_f for flexibility improved the resilience index $\bar{R}$ by approximately 5%, whereas similar perturbations in redundancy yielded less than 1% improvement. This finding highlights the dominant influence of agility-oriented enablers over capital-intensive redundancy-based strategies.

5.2 Managerial Insights

The results have several implications for practitioners in high-tech manufacturing and electric-vehicle supply chains:

- Investments in flexibility and visibility yield the highest resilience payoffs, particularly in globalized multi-tier networks.
- Digital transparency (real-time tracking and analytics) enhances early disruption detection and adaptive decision-making.
- Collaborative governance with suppliers mitigates recovery delays and reduces dependency risks.
- Excessive redundancy can inflate cost without proportionate resilience gains.
- The model's probabilistic–fuzzy outputs allow confidence-based prioritization, enabling managers to allocate resources to high-impact, high-certainty enablers.

6. Managerial and Theoretical Implications

6.1 Managerial Implications

The insights from the Type-2 Fuzzy Monte Carlo (T2F-MC) framework give managers in high-tech manufacturing—and really any disruption-heavy industry—something far more useful than a single resilience score. Traditional metrics tend to flatten uncertainty into one number, which can be misleading. In contrast, the T2F-MC model provides a full resilience distribution with confidence bounds, letting decision-makers plan with a clearer sense of how uncertain their situation actually is.

1. Prioritization of High-Impact Enablers

The sensitivity analysis shows that Supplier Flexibility and Visibility stand out as the most influential levers shaping overall resilience. This means managers should focus on expanding multi-sourcing options, qualifying backup suppliers, and strengthening digital visibility systems that track inventory and logistics in real time. Since the model quantifies the expected improvement for even small changes, firms can channel resources toward enablers that offer the highest marginal gain in resilience.

2. Strategic Balance Between Efficiency and Redundancy

While redundancy does help resilience, it doesn't pay off indefinitely. The T2F-MC results indicate that piling on extra buffers eventually yields diminishing benefits and inflates carrying costs—echoing long-standing managerial arguments (Sheffi, 2005). A smarter approach is selective redundancy, aimed at truly critical components instead of the entire system. With the shape of the resilience distribution available, managers can even set explicit confidence targets (for example, ensuring a 90% chance of achieving resilience ≥ 0.70) rather than relying solely on average scores.

3. Integrating Subjective Judgments in Data-Driven Decisions

High-tech industries often operate with incomplete data, leaving teams to rely on expressions like "high collaboration" or "moderate flexibility." The Type-2 fuzzy component captures the fuzziness and disagreement built into these expert opinions, giving firms a structured way to merge qualitative insights with quantitative modeling. This helps align the perspectives of technical analysts, engineers, and management teams who may otherwise interpret the same inputs very differently.

4. Scenario-Based Risk Preparedness

Because the T2F-MC model works through simulation, managers can easily test different what-if situations—longer supplier delays, policy shifts, or sudden capacity shortages. Watching how the fuzzy–probabilistic resilience curve changes across scenarios helps firms design strategies that are robust across multiple futures, not just one forecast.

5. Digital Transformation and Decision Support

Embedding the T2F-MC tool into spreadsheets or Python dashboards allows continuous tracking of resilience using live data streams. This fits naturally with digital-twin concepts in operations management, where simulations run alongside IoT-enabled monitoring. The model's fuzzy-stochastic outputs can also become Key Resilience Indicators (KRIs), complementing standard metrics like cost, service levels, and risk exposure.

6.2 Theoretical Contributions

Beyond managerial applications, this framework adds several conceptual advancements to resilience modeling and uncertainty research.

1. Integration of Dual Uncertainty Domains

The model brings epistemic (knowledge-related) and aleatory (random) uncertainty together in one computational structure—something rarely attempted in earlier studies. Prior work typically relied on probabilistic models assuming well-known distributions (Metropolis & Ulam, 1949) or on fuzzy systems ignoring randomness altogether (Zadeh, 1965). The T2F-MC approach sits between these extremes, offering a reusable blueprint for hybrid uncertainty analysis.

2. Operationalization of Deep Uncertainty

Drawing on Lempert et al. (2003) and Walker et al. (2013), this study turns deep uncertainty—where people disagree about models, probabilities, or preferences—into measurable analytical outputs. Interval Type-2 fuzzy sets reflect the lack of consensus in expert assessments, while PERT-based Monte Carlo sampling accounts for random variability. Together, they approximate how managers actually reason under incomplete and conflicting information.

6.3 Summary

By merging Type-2 fuzzy inference with Monte Carlo simulation, this framework shifts resilience assessment from static, deterministic scores to uncertainty-aware resilience analytics. For managers, it offers a way to allocate resources not just based on expected performance but also on how much uncertainty they are willing to tolerate. Theoretically, it strengthens the foundations for modeling deep uncertainty in supply-chain research and provides a scalable structure for future hybrid modeling efforts.

7. Conclusion and Future Work

This study developed and showcased a Type-2 Fuzzy Monte Carlo (T2F-MC) model for quantifying supply-chain resilience under two forms of uncertainty. By combining interval Type-2 fuzzy logic with PERT-based Monte Carlo simulation, the framework captures both epistemic uncertainty—coming from expert subjectivity and linguistic vagueness—and aleatory uncertainty, which reflects the natural randomness in supply-chain performance. The result is a unified computational setup that turns a mix of qualitative opinions and quantitative inputs into a resilience-index distribution complete with confidence bounds.

From a practical viewpoint, the study illustrates how hybrid fuzzy–stochastic modeling can support real-world decision making. Managers can explore the trade-offs between boosting resilience and reducing uncertainty, examine when redundancy investments are worth the cost, and check confidence levels before committing resources. Because the model works smoothly with Python or Excel, it remains transparent and easy to adapt within enterprise analytics workflows or digital-twin environments.

In conclusion, the Type-2 Fuzzy Monte Carlo model offers a fresh and flexible way to assess supply-chain resilience in uncertain settings. It shifts resilience evaluation away from fixed, deterministic scores toward confidence-aware analytics, allowing decision-makers to craft strategies that are both efficient and robust under deep uncertainty. By connecting managerial intuition with rigorous quantitative methods, the framework lays the groundwork for future research that blends fuzzy reasoning, stochastic simulation, and adaptive optimization into a cohesive approach to resilience engineering.

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