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AN INTELLIGENT AHP–MONTE CARLO DECISION FRAMEWORK FOR SUPPLY CHAIN RESILIENCE IN INDUSTRY 5.0

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ABSTRACT

Intelligent decision-support strategies are increasingly needed to assess supply chain resilience under uncertain operating conditions. Resilience, in the era of Industry 5.0, is built on the interaction between human expertise, advanced technologies, and adaptive manufacturing capabilities. This article presents an intelligent decision-support framework that combines the Analytic Hierarchy Process (AHP) with Monte Carlo Simulation (MCS) to evaluate supply chain resilience under uncertainty. It embeds Human–Machine Collaboration (HMC) and Additive Manufacturing (AM) as critical Industry 5.0 enablers. AHP is used to prioritize resilience dimensions, whereas Monte Carlo Simulation assesses disruption frequency, recovery time, and service-level variability across multiple disruption scenarios. The results identify Flexibility and Human Oversight as the dominant resilience drivers, where Sustainability plays a moderate role and Machine Efficiency and ESG Alignment have lower sensitivity. Simulation also shows that the combination of HMC and AM helps enhance resilience and improve recovery performance under moderate and severe disruptions. The proposed computational and probabilistic decision-support framework supports resilience evaluation and strategic decision-making in Industry 5.0-enabled supply chains.

Keywords: *Decision Support, Industry 5.0, Supply Chain Resilience, Analytic Hierarchy Process, Monte Carlo Simulation.*

1. INTRODUCTION

Current industrial systems operate in increasingly dynamic and uncertain environments, and effective intelligent decision-support technologies are necessary to maintain their performance and support strategic decision-making. With increasing complexity in industrial operations and the frequency of disruptions, the need for computational resources that can integrate structured decision-making and uncertainty analysis cannot be underestimated. In this sense, Industry 5.0 goes beyond the goals of earlier industrial paradigms by integrating new technologies with human knowledge, sustainability features, and adaptive operational capabilities. Additionally, recent studies have emphasized how Industry 5.0 technologies can help achieve net-zero and nature-positive supply chains [1]. Recent advances in digital connectivity, such as 5G-enabled industrial systems, further strengthen real-time coordination and decision-support capabilities for resilient supply chains [2]. Sustainability has emerged as a key component of Industry 5.0-oriented supply chains, especially in developing industrial contexts, according to recent empirical research [3].

Pandemics, geopolitical instability, resource shortages, transportation failures, and demand volatility have left global supply chains particularly vulnerable to disruptions. These disruptions have highlighted the shortcomings of highly optimized supply chain structures and the need for resilience assessment methods that support adaptive decision-making under uncertainty. Hence, digital technologies are increasingly essential in strengthening resilient and adaptive supply chains [4].

On the one hand, Additive Manufacturing (AM) is a strong technological enabler that encourages resilient supply chains through decentralized production, rapid product redesign, and localized manufacturing. Meanwhile, Human–Machine Collaboration (HMC) allows industrial systems to combine computational capabilities with human judgement, contextual interpretation, and adaptive decision-making. Together, these Industry 5.0 enablers are driving more dynamic and resilient industrial systems.

Despite the growing literature on supply chain resilience and Industry 5.0, several methodological and conceptual gaps remain. First, common resilience assessment approaches are based on deterministic indicators or multi-criteria decision-making methods that identify the relative importance of resilience capabilities but provide limited insight into how these priorities perform under different disruption scenarios. Second, probabilistic approaches are increasingly used to capture uncertainty; however, their integration with structured multi-criteria prioritisation remains limited, especially when resilience is assessed through operational, human-centered, technological, and sustainability dimensions simultaneously. Third, although human-centricity, technological capability, sustainability, and resilience are increasingly considered in Industry 5.0 research, they are typically analysed separately rather than integrated into a holistic quantitative decision-support framework. Thus, an important methodological gap remains between identifying the key resilience capabilities to be prioritised and evaluating the robustness of their combined contribution under uncertain disruption conditions.

This study addresses this gap by integrating the Analytic Hierarchy Process (AHP) with Monte Carlo Simulation (MCS) within an Industry 5.0 resilience framework. AHP provides a structured mechanism for prioritizing six resilience dimensions, whereas MCS evaluates the behavior of the resulting resilience configuration under stochastic disruption scenarios. Human–Machine Collaboration and Additive Manufacturing provide the Industry 5.0 context through which human and technological capabilities are jointly interpreted. The proposed integration therefore moves beyond static prioritization by linking strategic resilience priorities to probabilistic performance assessment under uncertainty.

Accordingly, the proposed intelligent decision-support framework provides a computational basis for assessing supply chain resilience under uncertainty within the Industry 5.0 context. The proposed framework contributes in three ways. First, it combines deterministic multi-criteria decision analysis with probabilistic simulation to provide a more comprehensive evaluation of resilience. Second, it incorporates human-centered and sustainability-oriented dimensions into computational resilience assessment. Third, it provides a decision-support mechanism capable of identifying the resilience factors that exert the greatest influence on system performance under different disruption scenarios.

The remainder of this paper is structured as follows. The conceptual framework for decision-support is introduced in Section 2. The development of the model and description of the problem are presented in Section 3. The integrated AHP–Monte Carlo approach is explained in Section 4. The simulation results and their discussion are presented in Section 5. Section 6 concludes the paper.

2. RELATED WORK

This study develops a computational decision-support framework for assessing resilience in Industry 5.0 supply chains. The proposed framework integrates HMC, AM, and probabilistic resilience assessment into a unified decision-support architecture. Rather than evaluating resilience as a static performance indicator, the framework combines human expertise, technological capabilities, and uncertainty modeling to support resilience-oriented decision-making in complex industrial systems.

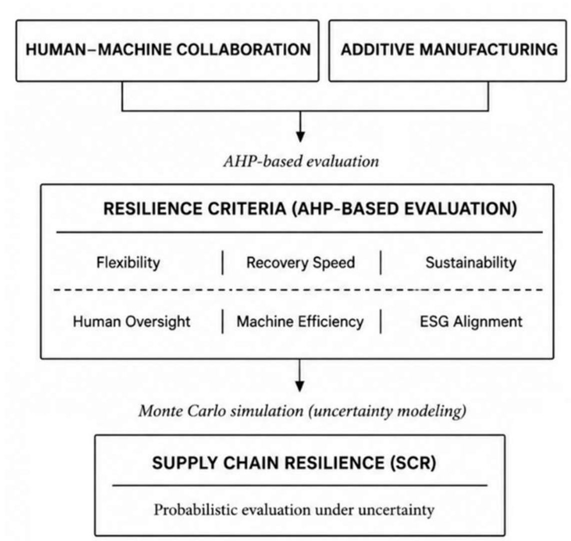

Figure 1: Conceptual framework for Industry 5.0 supply chain resilience integrating Human–Machine Collaboration and Additive Manufacturing

Figure 1 illustrates the overall computational architecture of the proposed framework, highlighting the interaction between Human–Machine Collaboration, Additive

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Manufacturing, and the resilience assessment process.

2.1 I5.0 & Human–Machine Collaboration

Industry 5.0 integrates human knowledge, cutting-edge technologies, and sustainability to support intelligent industrial decision-making environments. In contrast to the automation and process efficiency that characterize I4.0, I5.0 facilitates collaboration between human intelligence and advanced technologies [5], [6], [7], [8]. According to earlier research, the shift from Industry 4.0 to Industry 5.0 is based on digital technology-supported lean supply chain principles [9].

In order to increase industrial resilience, Industry 5.0 integrates cutting-edge digital technologies with human-centered decision-making, according to recent studies [10].

Within this paradigm, humans contribute contextual understanding, ethical judgment, and adaptive decision-making, while machines provide precision, speed, and computational capabilities.

Recent industrial evidence has shown that artificial intelligence contributes to improving operational coordination and decision-making in supply chain environments [11], [12].

HMC therefore represents one of the principal drivers of resilience [13], [14]. By combining human adaptation with technological capabilities, HMC enables supply chains to respond more efficiently during disruptions and uncertain operating conditions.

2.2 Additive Manufacturing and Supply Chain Resilience

Within computational decision-support environments, AM provides operational flexibility by enabling decentralized production, rapid reconfiguration, and localized manufacturing. These capabilities improve the responsiveness of resilient supply chains and strengthen adaptive decision-making during disruption scenarios [15]. These characteristics are also aligned with reconfigurable supply chain concepts that promote adaptive network structures during disruption [16]. Similarly, in contemporary supply chains, IoT-enabled digital infrastructures greatly improve visibility, coordination, and sustainability [17].

During disruptions, AM allows firms to reconfigure manufacturing processes, replace production materials, and maintain operations through local manufacturing. When combined with HMC, AM benefits from human oversight in decision-making, quality assurance, and sustainability considerations, which enhances overall system resilience.

2.3 Multi-Criteria Decision Analysis and Uncertainty Modeling

Assessing resilience in I5.0 supply chains requires the integration of structured decision-making techniques with uncertainty modelling. Recent studies have shown that combining risk assessment methods with uncertainty analysis provides a more comprehensive representation of supply chain behavior under disruptive conditions [18]. This integrated approach enables more robust and adaptive resilience-based decision-making. Multi-criteria decision analysis methodologies, particularly AHP, have long been applied to prioritize complex decision factors based on qualitative and quantitative criteria [19], [20], [21]. However, AHP gives a deterministic perspective and does not capture the stochastic nature of disruption-prone environments. MCS is used to model uncertainty and describe the response of the system to variations in multiple disruption scenarios [22], [23], [24].

By integrating AHP and MCS, the framework combines structured resilience prioritization with uncertainty analysis, providing a more realistic and adaptive assessment of supply chain resilience that is consistent with the characteristics of Industry 5.0 supply chains [19], [20], [22].

2.4 Integrated Conceptual Framework

The proposed framework combines HMC and AM as important enablers that affect essential elements of resilience—flexibility, recovery speed, sustainability, Human Oversight, machine efficacy, and ESG fit. These dimensions are evaluated using AHP to determine their relative importance and are then assessed through Monte Carlo Simulation under uncertainty.

A human-centric, technology-driven approach combined with a probabilistic systemic response strengthens the understanding of supply chain resilience. The following section then sets out the methodological framework.

2.5 Human–Machine–Supply Chain Integration

One of the fundamental components of I5.0 systems is the interaction of human, technological, and supply chain components. In this study, resilience results from the interdependence of these three dimensions, which are viewed as an integrated system.

The human element in Industry 5.0 and beyond includes contextual interpretation, ethical reasoning, and adaptive decision-making. These features are essential for handling complex disturbances that automated decision-making alone is unable to handle. Artificial intelligence, additive manufacturing, and digital technologies represent the technological dimension that enhances operational effectiveness, responsiveness, and production flexibility.

The supply chain aspect provides the integrative layer that translates human skills and technical expertise into coordinated, resilient, and sustainable operational outcomes.

Together, these dimensions enable resilient supply chains to dynamically accommodate disruptive impacts through human adaptability, scalable technological capabilities, and decentralized production. Additive manufacturing facilitates local production and rapid process reconfiguration, while human oversight provides contextual validation, strategic alignment, and informed decision-making.

Consequently, resilience is conceptualized as a multidimensional capability emerging from the interaction between human expertise, advanced technologies, and adaptive supply chain processes. This conceptual perspective provides the foundation for the computational model developed in the following section.

3. COMPUTATIONAL MODEL DEVELOPMENT AND PROBLEM FORMULATION

Building on the computational decision-support framework introduced in Section 2, this section formulates the computational model used to evaluate resilience within Industry 5.0 supply chains. The model integrates structured multi-criteria decision analysis with probabilistic uncertainty modeling to support resilience-oriented decision-making under disruption conditions.

Flexibility describes the system's adaptability towards dynamic environments, while recovery speed measures the time required to return to normal operations. Sustainability and ESG alignment reflect both environmental and social issues, while human oversight and machine efficiency characterize the relationship between human action and technology.

The relative importance of these criteria is assessed using the AHP [18], [21]. Thus, R is the Resilience Index defined as:

$$R = \sum_{i=1}^{n} w_i \cdot r_i \tag{1}$$

where w_i is the normalized AHP weight of criterion i, with i = 1, …, n, and $\sum_{i=1}^{n} w_i = 1$. The post-disruption performance (retention rate) of criterion i is represented by the variable $r_i \in [0,1]$, where $r_i = 1$ indicates total performance retention and $r_i = 0$ represents total performance loss. This provides a normalized aggregate summary of the multi-dimensional system's performance under various disruption situations.

However, because supply chain disruptions are stochastic, the values of the retention rates r_i remain uncertain. Monte Carlo simulation is used to model important variables, including service-level retention, recovery time, and disruption frequency, in order to account for this uncertainty. This probabilistic methodology allows resilience to be assessed as a dynamic response to disruption rather than as a strictly deterministic result. The following section provides a detailed description of the methodological implementation of Monte Carlo simulation and AHP.

4. COMPUTATIONAL METHODOLOGY

In order to facilitate resilience assessment and decision-making in I5.0 supply chains, this study develops an intelligent computational methodology that combines the AHP with MCS. The proposed approach models uncertainty and produces decision-support data for complex industrial environments by combining probabilistic simulation with deterministic multi-criteria evaluation.

The proposed framework considers the combined impact of HMC and AM on resilience performance during disruptive events. The strategy highlights the socio-technical character of Industry 5.0 systems, where human oversight, technological capabilities, environmental concerns, and adaptive decision-making interact to produce resilience. While Monte Carlo simulation provides probabilistic evaluation of how systems respond in uncertain times, AHP supports the structured prioritization of resilience indicators based on expert judgments [19], [20].

By combining deterministic multi-criteria decision analysis and stochastic simulation, the approach enables resilience to be assessed as a dynamic and probabilistic result rather than a static performance indicator.

Figure 2 illustrates the methodological process, which summarizes the interaction between Human–Machine Collaboration, Additive Manufacturing, and the integrated AHP–MCS resilience framework.

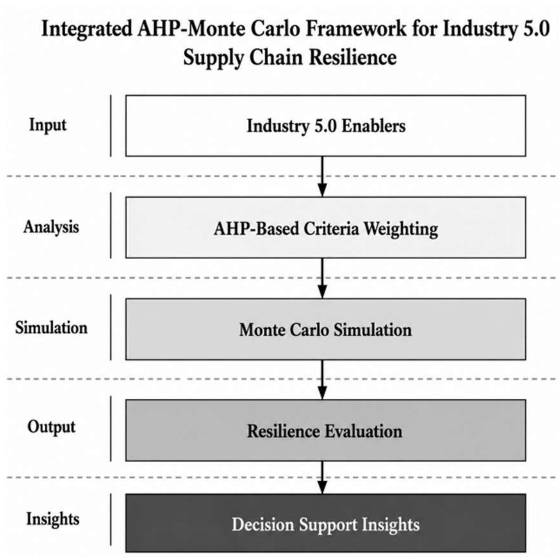

Figure 2: Integrated AHP–MCS framework for evaluating I5.0 SC resilience under uncertainty

4.1 Research design

The proposed computational framework consists of four sequential analytical stages that collectively support intelligent resilience evaluation.

Step 1: Criteria Identification: The first stage involves identifying the key resilience indicators relevant to Industry 5.0 supply chains. The criteria were adopted from common resilience dimensions found in recent literature concerning Industry 5.0, adaptive manufacturing systems, and human–machine collaboration [8], [13], [14].

Step 2: AHP Prioritization: The second stage applies AHP to build a hierarchical structure to the resilience problem, and make pairwise comparisons, derive normalized weights, and measure consistency.

Step 3: Monte Carlo Simulation: The third stage incorporates uncertainty into the resilience evaluation process through Monte Carlo Simulation. Disruption frequency, recovery behavior, and service-level variability are modeled probabilistically under multiple disruption scenarios.

Step 4: Integrated Resilience Evaluation: The final stage combines the deterministic AHP weights with the outputs of the stochastic simulation by building a composite Resilience Index as a representation of resilience behavior in uncertain operating domains.

The analytical architecture of the framework is sequential in design and therefore enables strategic prioritization and probabilistic evaluation to be assessed simultaneously, leading to increased methodological rigor and operational realism.

4.1.1 Expert Judgment Collection

The pairwise comparison matrix was developed using expert judgments from specialists in supply chain resilience, additive manufacturing, and Industry 5.0 systems. The aggregated evaluations were used to determine the relative importance of the resilience criteria.

4.2 Dataset Collection

4.2.1 Overview

Saaty developed the Analytic Hierarchy Process, which is one of the most widely used multi-criteria decision-making techniques for assessing both qualitative and quantitative factors. It enables complex decision problems to be structured into a hierarchy of criteria and sub-criteria. In this study, AHP is used to assess the relative importance of the resilience dimensions considered in Industry 5.0 supply chains [19], [20], [21].

Traditionally, AHP has been applied in supply chain management for supplier selection, risk assessment, operational planning, and transportation decision-making [20], [25]. AHP-based multi-criteria techniques have been effectively used in recent applications for strategic supply chain decision-making and sustainable supplier selection [26]. In contrast, the present framework incorporates human-centered and sustainability-related dimensions that have become increasingly important in Industry 5.0 environments.

4.2.2 Hierarchical Structure

The AHP hierarchy developed for this framework consists of three levels: the overall objective, the evaluation criteria, and the corresponding sub-criteria.

The objective is to assess the resilience of I5.0 supply chains under disruption and uncertainty. The framework considers six main criteria: flexibility (C1), recovery speed (C2), sustainability

(C3), human oversight (C4), machine efficiency (C5), and ESG alignment (C6). These criteria were selected to balance operational performance, sustainability objectives, and human-centered decision-making considerations. The subsequent hierarchy of the proposed model is illustrated in Figure 3.

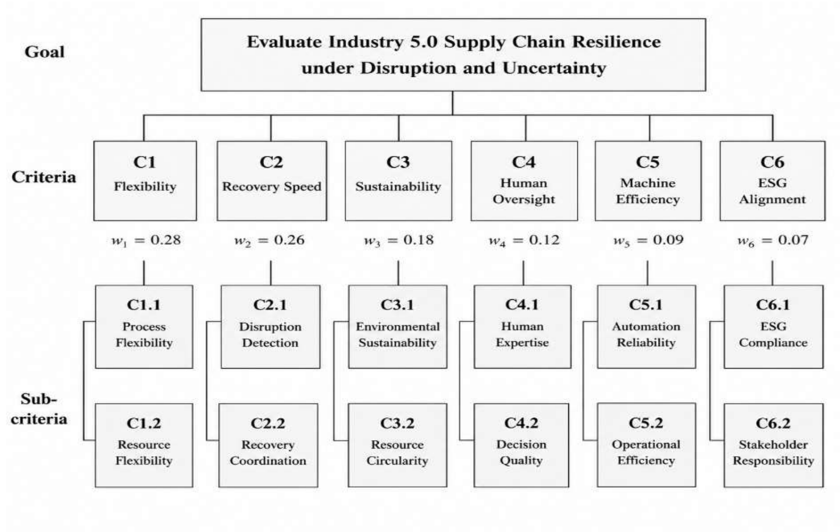

Figure 3: AHP hierarchical structure for evaluating Industry 5.0 supply chain resilience

4.2.3 Criteria Definition

Flexibility (C1): is the capacity of the supply chain to quickly reconfigure operational processes, supplier networks, production schedules, and resource allocation upon a disruption. In an Industry 5.0 context, flexibility is further consolidated by dynamic production systems and decentralized production that are made possible using Additive Manufacturing technologies [27].

Recovery Speed (C2): indicates how quickly the supply chain can return to operation after a disruption. It measures the return period of production, logistics and coordinating operations to an acceptable performance state after operational impairment. For Industry 5.0 systems, rapid recovery is closely related with flexible coordination of human decision-makers with intelligent production systems [28], [29].

Sustainability (C3): assesses the capability of the SC to operate environmentally and socially responsibly, in the event of disruption and after it happens. This includes resource use efficiency, waste reduction, energy optimization, circular production, and long-term operation potential. In Industry 5.0, sustainability is considered an inseparable component of resilience rather than an independent operational objective [30], [31].

Human Oversight (C4): represents the involvement of human judgment, contextual understanding, ethical reasoning, and supervisory decision-making within industrial systems. Unlike all-automated industrial models Industry 5.0 is not based on humans versus machines, but the interaction between human knowledge and intelligent technologies. As a result, human monitoring emerged as the crucial resilience force with an ability to increase adaptive decision-making under perturbations [6], [7], [13], [14]

Machine Efficiency (C5): assesses the performance of intelligent manufacturing systems in the areas of precision, throughput, automation, process reliability, or continuity of production. While Industry 5.0 represents a transition from only efficiency-based industrial paradigms, technological performance continues to play a critical role in strengthening resilience by ensuring operational stability in scenarios characterized by uncertainty [32], [33].

ESG Alignment (C6): the degree to which resilience strategies respect environmental, social and governance principles related to responsible supply chain management. This attribute mirrors growing emphasis on ethical conduct, stakeholder accountability and sustainability in the industrial sectors in Industry 5.0 settings [30], [34].

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4.2.4 Pairwise Comparison Matrix

To quantify the relative importance of the resilience criteria, AHP employs a pairwise comparison matrix: $A = [a_{ij}]$, $i, j = 1, \ldots, n$, where each element a_{ij} represents the relative importance of criterion i with respect to criterion j.

The matrix satisfies the reciprocal condition:

$$a_{ji} = \frac{1}{a_{ij}}, \qquad a_{ii} = 1$$

Saaty's 1–9 scale, where 1 denotes equal relevance and 9 denotes great importance, was used for pairwise comparisons [19].

Saaty's core scale, which is based on structured expert judgements and resilience priorities found in the I5.0 and SC resilience literature, was used to create the pairwise comparison matrix.

An illustrative pairwise comparison matrix is presented in Table 1.

Table 1: Pairwise comparison matrix of resilience criteria based on expert judgments using the Saaty scale.

Resilience Criteria	C1	C2	C3	C4	C5	C6
C1 Flexibility	1.00	2.00	2.00	1.00	4.00	4.00
C2 Recovery Speed	0.50	1.00	0.50	0.50	2.00	2.00
C3 Sustainability	0.50	2.00	1.00	0.50	2.00	2.00
C4 Human Oversight	1.00	2.00	2.00	1.00	3.00	3.00
C5 Machine Efficiency	0.25	0.50	0.50	0.33	1.00	1.00
C6 ESG Alignment	0.25	0.50	0.50	0.33	1.00	1.00

4.2.5 Weight Derivation and Consistency Analysis

After the pairwise comparison matrix is constructed, the eigenvector approximation approach is used to produce normalized weights.

Column Normalization:

Each matrix element is normalized as:

$$a'_{ij} = \frac{a_{ij}}{\sum_{k=1}^{n} a_{kj}} \tag{2}$$

Row Averaging:

The normalized weight associated with criterion i is computed as:

$$w_i = \frac{1}{n}\sum_{j=1}^{n} a'_{ij}, \qquad \sum_{i=1}^{n} w_i = 1 \tag{3}$$

The resulting weight vector: $w = [w_1, w_2, \ldots, w_6]^T$ represents the relative contribution of each criterion to overall resilience.

To evaluate the consistency of the judgments, the maximum eigenvalue is computed as:

$$\lambda_{\max} = \sum_{i=1}^{n} \frac{(A\mathbf{w})_i}{n w_i} \tag{4}$$

The Consistency Index (CI) and Consistency Ratio (CR) are then calculated:

$$CI = \frac{\lambda_{\max} - n}{n-1}, \qquad CR = \frac{CI}{RI}$$

where RI denotes Saaty's Random Index. The comparison matrix is considered consistent when: CR < 0.10 [19], [20].

In this study, the consistency ratio was found to be CR = 0.0109, which is well below the acceptable threshold of 0.10 and therefore confirms the consistency of the pairwise comparisons.

4.2.6 Resilience Index Formulation

By combining the post-disruption performance of the selected criteria, a composite Resilience Index (R) is created to assess supply chain resilience under disruption situations. The Resilience Index is defined as in Equation (1):

$$R = \sum_{i=1}^{n} w_i \cdot r_i$$

Let w_i denote the normalized AHP weight associated with criterion i, where i= 1,…,n and $\sum_{i=1}^{n} w_i = 1$ with n = 6. Let $r_i \in [0,1]$ be the retention rate of criterion i, defined as the proportion of its performance maintained after disruption (with r_i=1 indicating no degradation and r_i=0 indicating complete failure).

By definition, R∈ [0,1] offers a normalized and comprehensible measure of system performance in challenging circumstances. Greater resilience and

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a better capacity to sustain operational performance across several dimensions are indicated by higher R values. AHP's deterministic prioritization and Monte Carlo simulation's probabilistic evaluation are connected via the Resilience Index.

4.3 Monte Carlo Simulation (MCS)

4.3.1 Rationale

Real-world supply chains function in extremely unpredictable and dynamic situations, despite AHP's structured and deterministic prioritization of resilience criteria. Numerous causes of variability, such as operational disruptions, recovery uncertainty, demand variations, and human decision-making variability, affect resilience in Industry 5.0 contexts.

In these circumstances, the stochastic behavior of resilience cannot be sufficiently captured by deterministic analysis alone. In order to overcome this restriction, Monte Carlo simulation represents system variability and uncertainty by repeated stochastic sampling [22], [24].

In contrast to deterministic approaches, Monte Carlo simulation produces a distribution of resilience outcomes that enable the assessment of system robustness under disruption, unpredictability, and expected performance. The resilience evaluation process can therefore go beyond static prioritization based on past performance by using Monte Carlo simulation, which also makes it possible to explicitly explain the uncertainty brought about by supply chain disruptions. The use of 10,000 iterations supports statistical stability and convergence of the simulation outputs, and the chosen stochastic distributions represent disruption features frequently covered in the supply chain resilience literature. This method improves the resilience assessment's credibility and robustness.

The stochastic modelling process adheres to accepted Monte Carlo simulation methods [22], [23], [24], while the simulation parameters were created based on disruption characteristics frequently reported in supply chain studies [28], [29].

4.3.2 Simulation Framework

The simulation framework was implemented using a spreadsheet-based Monte Carlo approach with 10,000 iterations to ensure statistical stability and consistency of resilience estimates. Three disruption scenarios were considered:

S1. Mild Disruption: Short-term logistics disruption involving transportation delays and temporary material shortages.

S2. Moderate Disruption: Equipment failure or regulatory interruption leading to supplier shutdown.

S3. Severe Disruption: Geopolitical disruption and demand surges affecting multiple supply chain layers. The simulation incorporates three stochastic variables:

$$Df \sim \text{Poisson}(\lambda)$$

$$T_r \sim \mathcal{N}(\mu, \sigma^2)$$

$$SL \sim \text{Beta}(\alpha, \beta)$$

Where Df represents disruption frequency, Tr denotes recovery time, and SL corresponds to service-level retention. The parameter λ represents the disruption frequency rate, μ and σ denote the mean and standard deviation of recovery time, respectively, and α and β define the shape parameters of the service-level Beta distribution.

The scenario-specific parameters are summarized in Table 3.

Table 3: MCS parameters under disruption scenarios

Scenario	λ	μ (days)	σ	α	β
Mild	2	5	2	8	2
Moderate	4	15	5	6	4
Severe	6	30	10	5	5

Based on disruption trends often observed in the industry-focused supply chain resilience literature recently, the simulation parameters were chosen and contextualized specifically against Industry 5.0-enabled factories [28], [29].

4.3.3 Simulation Iterations and Output Analysis

For each simulation run k, resilience is computed as:

$$R^{(k)} = \sum_{i=1}^{n} w_i \, \mathrm{r}_i^{(k)} \tag{5}$$

where w_i denotes the AHP-derived weight of criterion i, $R^{(k)}$ denotes the resilience score at iteration k and $\mathrm{r}_i^{(k)}$ denotes the sampled retention rate of criterion i at iteration k.

As shown in Section 4.3.2, the expected level of resilience is then estimated to be:

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$$R^* = \frac{1}{N}\sum_{k=1}^{N} R^{(k)} \quad (6)$$

This approach generates a distribution of potential resilience outcomes rather than a single deterministic estimate, providing a more comprehensive representation of system behavior under uncertainty.

Statistical analysis is subsequently performed to estimate the mean resilience level, standard deviation, percentile ranges, confidence intervals, and scenario-based variability.

Sensitivity analysis is additionally performed by perturbing input parameters within a ±10% distance while monitoring change in Resilience Index over time. The analysis shows that Flexibility and Human Oversight are the leading causes in resilience variability followed by Sustainability and Recovery Speed.

The MCS was conducted through 10,000 iterations in each of the disruption scenarios. Stochastic values were calculated for frequency of the disruptions for each iteration, recovery time, and service-level retention respectively, and a Resilience Index was derived using these results from all of the AHP-derived weights. Simulation outputs include resilience mean values, variability score, percentile ranges, scenario comparisons and sensitivity analysis.

4.4 Integrated AHP–MCS Framework

The proposed computational decision-support framework combines deterministic prioritization through AHP with probabilistic uncertainty modeling through Monte Carlo Simulation. The integration of these complementary approaches enables resilience evaluation under multiple disruption scenarios while providing decision-support information for adaptive industrial systems operating within Industry 5.0 environments. The framework consists of four computational layers:

1.Criteria prioritization

2.Resilience Index formulation

3.Probabilistic simulation

4.Scenario-based resilience evaluation

These four computational layers enable resilience to be assessed from strategic, operational, probabilistic, and human-centered perspectives, providing a comprehensive computational framework for resilience-oriented decision-making.

Unlike conventional resilience assessment approaches that primarily focus on operational performance, our theoretical lens merges human-centered Industry 5.0 principles with probabilistic methods of resilience assessment. This integration extends resilience analysis beyond technical performance by accounting for adaptive coordination, uncertainty propagation, and human–machine interaction under disruption conditions [5], [28], [33]. As such, the framework contributes to the resilience literature by combining multi-criteria decision analysis with stochastic modeling to offer a broader perspective about resilience under uncertainty.

The purpose of the proposed model is not to reproduce the full complexity of industrial supply chains, but to provide a clear and extensible decision-support model that can be adapted to specific firm applications.

4.5 Computational Validation Framework

A practical scenario-based numerical simulation technique was applied for evaluating the stability of the proposed framework under uncertainty. We aimed to replicate authentic modes of disruption to understand the robustness of the framework to different operating conditions.

Monte Carlo simulation was performed using 10,000 iterations for each disruption scenario. Stochastic values were generated for the main disruption variables, including the frequency of disruption in each iteration, the time to recover on demand, and retention at service levels. They were further considered as probabilistic distributions with a mild to severe severity variation in disruptions.

For each iteration the Resilience Index was calculated by combining AHP-calculated weights and simulated resilience criterion performance scores. This approach allows us to assess the relative importance of resilience dimensions and the diversity of resilience dimensions in ambiguous contexts.

The simulation was developed in a spreadsheet-based environment, achieving transparency, reproducibility, and ease of implementation. The outputs include mean resilience values, variability measures, and scenario comparisons, providing a summary of supply chain resiliency development.

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The proposed framework was evaluated through an extensive scenario-based computational experiment involving 10,000 Monte Carlo iterations under three disruption scenarios. Although empirical industrial datasets were not available, the simulation parameters were defined according to disruption characteristics reported in recent supply chain resilience literature. Consequently, the framework provides a reproducible computational environment for evaluating resilience under uncertainty.

5. RESULTS AND DISCUSSION

5.1 AHP Results and Criteria Prioritization

The proposed computational decision-support framework applies the AHP to determine the relative importance of the resilience criteria. The normalized weights provide the deterministic basis for the subsequent probabilistic resilience assessment performed through Monte Carlo Simulation. A pairwise comparison matrix was constructed using the six resilience criteria: Flexibility, Recovery Speed, Sustainability, Human Oversight, Machine Efficiency, and ESG Alignment. The relative weights were then derived through the AHP normalization procedure. The reliability of the pairwise judgments was verified through consistency analysis, with the Consistency Ratio (CR) remaining well below the acceptable threshold of 0.10.

The normalized weights obtained from AHP analysis are detailed in Table 2.

Table 2: Normalized AHP weights of resilience criteria.

Criterion	Normalized Weight
Flexibility	0.291
Human Oversight	0.264
Sustainability	0.163
Recovery Speed	0.129
Machine Efficiency	0.076
ESG Alignment	0.076

Table 2 shows that Flexibility (0.291) and Human Oversight (0.264) are the most influential criteria, followed by Sustainability (0.163). Recovery Speed exhibits moderate importance (0.129), whereas Machine Efficiency (0.076) and ESG Alignment (0.076) make the smallest contributions. The distribution of the priority weights is further illustrated in Figure 4.

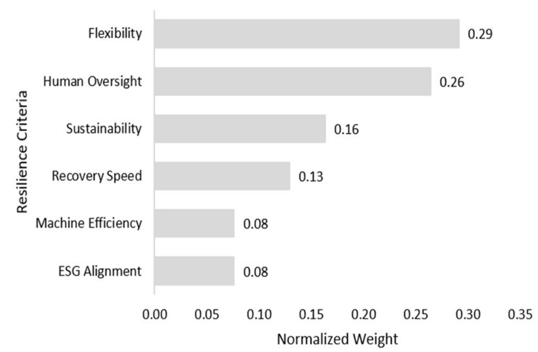

Figure 4: Normalized AHP weights of resilience criteria

The findings suggest that Flexibility and Human Oversight stand as the two core factors of the proposed resilience dimensions. Flexibility is a key driver for operational rapid reconfiguration, under disruptive stress, in a decentralized and adaptive production configuration. AM offers significant potential for enabling responsive production processes at the local level.

Human Oversight also plays a significant role in resilience performance. Even though intelligent systems are used more extensively, human-centered intervention is still required to interpret context and reason flexibly to coordinate the strategy involved in events of disruption [13], [14]. This discovery reinforces the human-centered nature of Industry 5.0, prioritizing resilience through the interaction of human skills with technological systems.

Another key finding concerns the role of Sustainability for overall resilience performance which reveals how resilient supply chains are expected to operate more sustainably from environmental and social factors as well as operational continuity [30], [31]. This indicates that sustainability models are becoming more mainstreamed into resilience-oriented decision-making processes.

In contrast, Machine Efficiency and ESG Alignment have a relatively limited short-term effect. Both of these components are beneficial to achieving long-term performance and regulatory compliance, but their response to disruptions is delayed as compared to adaptive and human-centered approaches. Recovery Speed occupies an intermediate position, reflecting the importance of restoring operations after disruptive events.

Finally, the above results and other found results suggest that AHP-induced resilience under Industry 5.0 will have mainly flexibility, human-centered decision making with human-centered management and sustainability-oriented activities as the basis of resilience. These findings provide the analytical basis for the subsequent Monte Carlo Simulation, which examines whether these priorities remain robust under uncertainty.

5.2 Monte Carlo Simulation Results

Monte Carlo Simulation was used to evaluate the probabilistic behavior of the proposed computational framework under uncertainty. Through simulation, such resilience distributions are generated, delivering decision-support information on system performance under multiple disruption scenarios.

Table 4: Statistical summary of Monte Carlo simulation outputs.

Statistic	Value
Mean	0.72
Median	0.71
Standard Deviation	0.10
5th Percentile	0.50
95th Percentile	0.90
Number of Iterations	10,000

The probability distribution of the simulated resilience scores is illustrated in Figure 5.

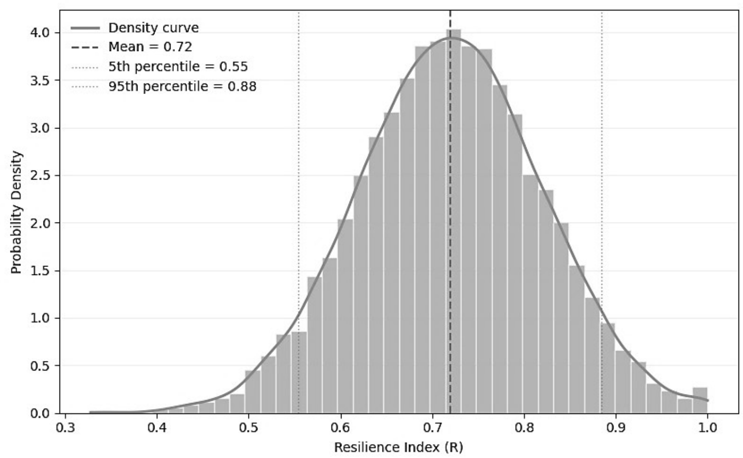

Figure 5: Probability distribution of the resilience index obtained from Monte Carlo simulation

The simulation results show that the industry 5.0-enabled framework maintains a relatively high level of resilience under uncertain conditions. The average resilience score was 0.72, with a standard deviation of 0.10, indicating moderate variability across simulation runs. The resilience scores are largely within the range defined by the 5th and 95th percentiles, meaning that most simulated outcomes are within acceptable operational limits.

The mean resilience value achieved (0.72) is indicative of the combined effect that moderate disruption frequency and variability in recovery time have on the stability of the performance.

Compared with conventional supply chain configurations reported in the literature, the achieved resilience level indicates strong system stability under uncertainty and supports the beneficial role of integrating Human–Machine Collaboration and Additive Manufacturing [28], [29], [35].

Moderate system sensitivity, with controlled stochastic variability over conditions of uncertain operation, is implied by the obtained variability ($\sigma = 0.10$). However, resilience variability increased under severe disruptions, indicating greater system sensitivity to high-intensity disturbances. This also shows how disruptions affect different aspects of the supply chain, including recovery time and service-level retention.

Finally, percentile analysis here strengthens our view of this framework as a probabilistic structure. For example, lower percentile scores reflect less favorable resilience outcomes, whereas higher percentiles represent more stable operating conditions and higher resilience levels. However, in reality, the majority of simulated solutions are still mainly well-focused on stable operational ranges. Industry 5.0-enabled systems show improved resilience performance when HMC and AM are integrated compared with the baseline.

Under moderate and severe disruptions, such systems typically achieve better resilience scores and greater stability. This is indicative of successfully integrating adaptive manufacturing technologies with the human-oriented decision-making process, thereby increasing the resilience of the supply chain.

5.3 Scenario Analysis

To assess the robustness of the developed computational framework, three perturbation situations, corresponding to different uncertainty levels, were simulated. This scenario analysis serves to show the ability of the decision-support framework to assess the resilience response to incremental disruption intensity.

Table 5 presents the comparative resilience performance across these disruption scenarios.

Table 5: Comparative resilience performance under disruption scenarios.

Scenario	Mean Resilience	Recovery Time (days)	Service Level
Mild	0.82	5	0.90
Moderate	0.73	15	0.75
Severe	0.66	30	0.60

The corresponding results are illustrated in Figure 6.

Figure 6: Impact of disruption severity on the mean resilience index

We find that in the context of increased levels of disruption intensities, performance decreases with resilience. In summary, the mild disruption scenario has the highest resilience level, with a mean resilience score of 0.82, brief recovery period (5 days), and high service (0.90). In such a context, the system maintains stable operational performance with its flexible production processes and coordinated Human–Machine Collaboration.

The reduction is mainly due to an increase in disruption frequency and longer recovery time for each scenario, which influences service-level retention and the stability of the system.

For the moderate scenario, resilience decreases to 0.73, then recovery time rises (15 days) and then down to (0.75) service level. These declines represent the impact of extended operational disruptions and shortages of supply. Additive Manufacturing reduces this effect by enabling local and decentralized production, while Human Oversight enables adaptive decision-making and resource reallocation. The severity of the scenario has the lowest resilience (0.66) with a considerably prolonged recovery time (30 days) due to high-intensity disruption imposed by the simulated environment.

This drop correlates with scenarios where multiple components of the supply chain fail at once. The rise in variability in this case results in a higher sensitivity of the system toward the propagation of the disruption. Similar disruption propagation mechanisms have been discussed by Ivanov and Dolgui [26], who showed that ripple effects substantially influence recovery performance across interconnected supply chain networks.

Despite this reduction, the proposed framework maintains higher resilience levels than conventional configurations, highlighting the benefits of integrating HMC and AM. Moreover, we find that the results are also in agreement with the sensitivity analysis, which shows Flexibility exerts more influence ($\Delta R = 0.16$), confirming that Flexibility is the most important part of resilience variability in scenarios [27], [28], [35].

Nevertheless, the scenario analysis shows that the design framework is still very well suited for a more moderate or severe disruption regime where adaptive coordination and decentralized production have become indispensable for the continuity of operations.

5.4 Sensitivity Analysis

Sensitivity analysis was conducted to evaluate the robustness of the computational decision-support framework and to identify the resilience criteria exerting the greatest influence on the computed Resilience Index.
Table 6 presents the sensitivity results of the resilience criteria.

Table 6: Sensitivity analysis of resilience criteria.

Rank	Criterion	ΔR (±10%)	Relative Influence
1	Flexibility	0.16	High
2	Human Oversight	0.14	High
3	Sustainability	0.10	Moderate
4	Recovery Speed	0.07	Moderate
5	Machine Efficiency	0.05	Low
6	ESG Alignment	0.05	Low

The corresponding tornado diagram is illustrated in Figure 7.

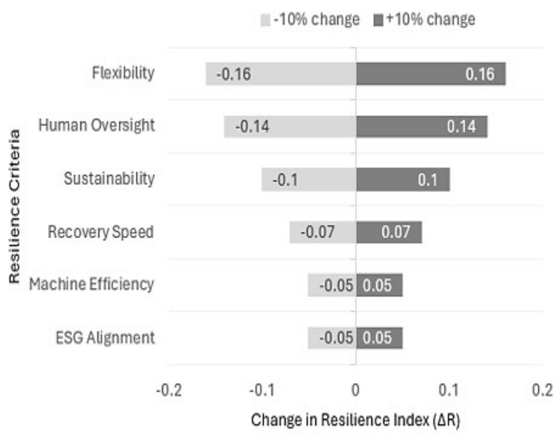

Figure 7: Sensitivity of the resilience index to ±10% variations in criteria weights

The results indicate that Flexibility and Human Oversight are the most important factors from the perspective of the model, with the ΔR value being 0.16 and 0.14 for Flexibility and Human Oversight respectively. Small variations in these performance criteria significantly affect the Resilience Index, reflecting their dominant influence on system resilience. This finding highlights the relevance of adaptive operational capability and human-centered decision-making in the context of I5.0 supply chains.

The role of flexibility (ΔR = 0.16) suggests that the resilience of I5.0 supply chains is led by adaptive reconfiguration capabilities rather than reactive recovery mechanisms.

Sustainability has a moderate degree of sensitivity (ΔR = 0.10), which demonstrates that it is a meaningful contributor to resilience performance. Thus, environmental and social resilience dimensions contribute to operational continuity and overall resilience performance.

Machine Efficiency and ESG Alignment have lower sensitivity (ΔR = 0.05), indicating limited immediate effects on variability. Although both measures remain relevant to long-term performance and compliance, their short-term influence on disruption response is lower than that of adaptive and human-centered dimensions. The moderate impact of Recovery Speed indicates its contribution to system recovery following disruptions.

In conclusion, the sensitivity analysis supports the robustness of the proposed framework and identifies Flexibility, Human Oversight, and Sustainability as key contributors to resilience in Industry 5.0 supply chains.

5.5 Discussion

It is evident from the findings that this computational decision-support framework can effectively evaluate resilience as a dynamic feature under uncertain operating conditions. The framework integrates deterministic multi-criteria analysis, probabilistic simulation, and multiple resilience dimensions to assess their importance and behavior across several potential disruption scenarios. This computational approach enhances traditional resilience frameworks by directly incorporating uncertainty into resilience analysis to support more informed decision-making in Industry 5.0 settings.

Flexibility showed the highest weight and sensitivity among the criteria examined. This finding means that a supply chain able to quickly respond and change production plans or reallocate resources or modify suppliers' configuration may adapt well to disruption. This adaptability is enhanced in an Industry 5.0 setting by decentralized responsive manufacturing methodologies supported by Additive Manufacturing [15], [27]. Furthermore, recent research has demonstrated that IoT-enabled intelligent inventory management systems enhance industrial supply chains' operational flexibility, visibility, and adaptive decision-making [36].

This is supported by past research on SC resilience. Ivanov and Dolgui [28] highlighted that operational flexibility is a fundamental capability for sustaining SC viability in adverse circumstances. Resilience-oriented manufacturing has increasingly been associated with production flexibility. In this regard, Belhadi et al. [27] reported that Additive Manufacturing strengthens resilience by facilitating rapid production reconfiguration, decentralized manufacturing, and faster recovery following disruptions. The outcomes obtained in this study align with those observations and further highlight flexibility as one of the fundamental capabilities supporting resilient Industry 5.0 systems.

In addition to operational flexibility, the analysis highlights the significance of human oversight. Although intelligent technologies significantly increase process efficiency, disruptive circumstances often contain uncertainties that call for judgement, experience, and contextual interpretation in addition to established algorithmic solutions. The findings show that resilient supply chains perform better when human decision-makers and intelligent technology work in tandem rather than in place of human expertise. This finding is in line with previous research [7], [13], [14].

This result also aligns with the broader Industry 5.0 perspective. Recent research examining cutting-edge digital technology as facilitators of manufacturing resilience in disruptive situations has revealed similar findings [37]. Nahavandi [7] and Sony and Naik [14] emphasized that human involvement is still essential for managing AI-driven decisions, evaluating complicated operational situations, and addressing ethical issues. Similar conclusions are reached by the current approach, which shows that human participation significantly increases resilience when supply chains function in uncertain environments. Similar findings were published by Belhadi et al. [38], who demonstrated that when organizational capabilities and well-informed human decision-making are present, the contribution of AI to SC resilience becomes significantly stronger.

The findings are broadly consistent with recent developments in the Supply Chain 5.0 literature, while also extending them through a quantitative uncertainty-based assessment. Recent research has emphasized adaptability, collaboration, and human-centered capabilities as central elements of resilient Industry 5.0 systems. For instance, recent Industry 5.0 resilience studies identify collaboration, technological resilience, and adaptive organizational capabilities among the most influential factors for maintaining performance under disruption. Similarly, empirical research on human–machine synergy indicates that digital capabilities and organizational flexibility can strengthen supply chain agility and adaptation [39]. These observations are consistent with the present results, in which Flexibility and Human Oversight exhibit the highest sensitivity to resilience performance. However, the present study goes further by quantifying their relative influence within an integrated AHP–Monte Carlo framework rather than examining these capabilities only conceptually or through deterministic prioritization.

In contrast to human oversight and flexibility, sustainability has a lower direct impact on the resilience index. However, its contribution is still important since social and environmental goals support industrial systems' long-term resilience. This result is consistent with Industry 5.0 principles, which call for productivity, sustainability, and human-centricity to develop as complementary aspects rather than as separate goals [8], [30], [31], [34].

The moderate contribution of Sustainability observed in the present framework also reflects recent Industry 5.0 research, which increasingly treats sustainability, resilience, and human-centricity as interconnected rather than independent objectives [40], [41]. Recent studies on Supply Chain 5.0 have shown that sustainability-oriented practices and human–machine collaboration can reinforce long-term resilience, although their immediate effects may differ according to disruption severity and organizational context. In parallel, recent Monte Carlo-based supply chain resilience research demonstrates the value of stochastic simulation for testing resilience strategies across disruptions of different severity. The present framework complements these studies by combining such probabilistic evaluation with AHP-derived strategic priorities, thereby linking the relative importance of resilience capabilities to their behavior under uncertainty.

Additionally, the simulated studies show that resilience gradually declines as disruption severity rises. However, the proposed system maintains relatively consistent performance even under severe disruption. Such behavior implies that integrating human-centered decision-making with adaptive production capacities improves recovery from unforeseen events as well as shock absorption.

This finding is also consistent with recent resilience research employing Monte Carlo Simulation to represent disruptions of varying severity and evaluate supply chain resilience strategies under stochastic conditions [42]. Unlike such simulation-centered approaches, the present study couples stochastic disruption analysis with AHP-derived resilience priorities, thereby linking uncertainty assessment with structured multi-criteria decision support.

A critical interpretation of these results is nevertheless necessary. The dominance of Flexibility and Human Oversight should not be interpreted as evidence that the remaining resilience dimensions are of secondary importance in all supply chain contexts. Their relative influence partly reflects the expert-derived AHP weights, and the disruption conditions represented in the simulation model. Under different industrial settings, expert panels, or disruption profiles, Sustainability, Machine Efficiency, or ESG Alignment may assume greater importance. Moreover, the relatively stable resilience performance observed across the simulated scenarios demonstrates the analytical robustness of the proposed configuration under the defined assumptions, but it should not be interpreted as evidence of universal resilience performance. The findings therefore support the usefulness of the framework as a comparative decision-support mechanism rather than as a fixed prescription for resilience priorities across all Industry 5.0 supply chains.

From a methodological perspective, combining MCS with the AHP offers a comprehensive approach for evaluating resilience. While Monte Carlo simulation captures the random character of disruption occurrence, recovery duration, and service-level retention, the AHP uses structured multi-criteria decision analysis to determine the relative relevance of resilience criteria. Rather than being represented by a single deterministic value, resilience can be evaluated as a dynamic phenomenon that changes under uncertainty thanks to their joint use.

Previous studies have confirmed the efficacy of this combined approach. Kroese et al. [22] and Rubinstein and Kroese [24] showed that Monte Carlo simulation is useful for analyzing system behavior under stochastic conditions and representing uncertainty. The proposed framework expands on conventional resilience evaluation by combining probabilistic simulation with AHP-based prioritization, providing a more thorough foundation for decision-making in challenging industrial settings.

The findings also emphasize the need for organizations to invest not only in technology but also in coordination, adaptation, and practitioners' ability to make well-informed decisions. Strengthening these capabilities can improve resilience performance in increasingly uncertain supply chain environments.

The findings provide a direct response to the objectives defined in this study. First, the AHP analysis successfully established a structured prioritization of the six resilience dimensions, identifying Flexibility and Human Oversight as the most influential criteria. Second, the Monte Carlo analysis demonstrated how the resilience configuration behaves under increasing levels of disruption uncertainty, thereby extending the assessment beyond a purely deterministic evaluation. Third, the integrated AHP–MCS framework showed that human-centered and technological resilience capabilities can be assessed jointly within a common decision-support structure. However, these achievements should be interpreted within the boundaries of the computational design. The results demonstrate the internal consistency and analytical usefulness of the framework, but they do not yet establish its performance across different industrial sectors or firm-specific operating environments.

Finally, the presented computational decision-support framework shows that the combination of formal multi-criteria analysis with probabilistic simulation approaches as proposed here is a powerful, versatile and scalable strategy to measure supply chain resilience under uncertainty. It draws on human expertise, technological capabilities, and stochastic modelling within an Industry 5.0 framework, offering theoretical insights and practical support for resilience-related decisions in complex industrial environments.

The proposed framework differs from prior resilience assessment approaches in three main respects. First, rather than relying solely on deterministic multi-criteria prioritization, it combines AHP with Monte Carlo Simulation to connect strategic importance weights with stochastic performance evaluation under disruption. Second, the framework explicitly incorporates Human Oversight alongside operational, technological, sustainability, and ESG-related resilience dimensions, thereby reflecting the human-centric orientation of Industry 5.0. Third, the model does not treat resilience criteria as isolated indicators; instead, it integrates them within a single composite resilience index that can be examined across different disruption severities. This combination provides a structured bridge between qualitative expert prioritization and quantitative uncertainty analysis, which remains comparatively limited in the existing Industry 5.0 resilience literature.

Despite the contribution of the proposed framework, several issues remain open. First, the AHP weights depend on expert judgments and may therefore vary according to the composition and experience of the expert panel. Second, the Monte Carlo analysis relies on predefined probability

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distributions and disruption scenarios, which simplify the complexity of real supply chain environments. Third, the interactions among resilience dimensions are represented through an additive aggregation model, whereas real-world relationships may involve dependencies and nonlinear effects. Finally, the framework has not yet been validated across multiple industrial sectors using firm-specific operational data. Future research should therefore examine the sensitivity of the framework to alternative expert panels and probability distributions, incorporate dependencies among resilience dimensions, and conduct empirical validation in different Industry 5.0 supply chain contexts.

6. CONCLUSION

This study proposed an intelligent decision-support framework integrating the Analytic Hierarchy Process (AHP) and Monte Carlo Simulation (MCS) to assess supply chain resilience within an Industry 5.0 context. The framework was designed to connect structured prioritization of resilience dimensions with probabilistic evaluation under disruption uncertainty while incorporating Human–Machine Collaboration and Additive Manufacturing as key Industry 5.0 enablers.

The findings indicate that Flexibility and Human Oversight are the most influential resilience dimensions within the considered configuration, followed by Sustainability, while Machine Efficiency and ESG Alignment exert a lower short-term influence on the computed resilience outcome. The Monte Carlo analysis also suggests that resilience decreases with increasing disruption severity, while the proposed framework remains relatively stable across simulated scenarios of the system. These findings support the hypothesis that resilient Industry 5.0 supply chains rely not only on technological capability but also on organizational flexibility and human involvement in decision-making.

For the authors, the key contribution of our framework is the ability to link the strategic resilience objectives to performance indicators based on uncertainty. Rather than being represented by a single measure, resilience should be considered as an evolving outcome shaped by human, technological, sustainability, and operational dimensions. This provides a more realistic basis for decision-making in disruption-prone environments.

However, the conclusions must be interpreted within the boundaries of the study. The AHP weights are based on expert judgments, the Monte Carlo model relies on predefined probability distribution and disruption scenarios, and the framework has not yet been applied to firm-specific operational data in various industrial sectors. These limitations restrict the generalization of the numerical results and show that the framework should be viewed not as a universal resilience prescription but as an adaptable decision-support framework for industrial decision-making.

Therefore, future research should validate the framework using empirical industrial datasets, investigate the sensitivity of the results to alternative expert panels and stochastic assumptions, consider dependencies among resilience dimensions, and extend the approach to other Industry 5.0 supply chain contexts. Overall, the study demonstrates that the integration of structured multi-criteria analysis and probabilistic simulation offers a practical and extensible basis for assessing supply chain resilience under uncertainty while retaining the human-centric focus of Industry 5.0.

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