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A House of Resilience Framework for Designing Resilient Logistics Systems: Conceptual Development and Application in Procurement

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Highlights

Please indicate how your work links to systems science via your contributions to systems practice, theory, and or methodology.

- The House of Resilience conceptualizes logistics resilience as an emergent system property resulting from interactions among technological, operational, structural, and strategic layers.
- The FHOR-RAM model operationalizes this architecture through hierarchical fuzzy inference, representing uncertainty, nonlinear relationships, and interdependencies among resilience dimensions.

What are the main findings and/or the implications of the main findings?

- The model enables an integrated diagnosis of resilience by identifying how weaknesses in individual layers constrain the resilience of the entire logistics system.
- Coordinated improvement across multiple resilience layers is more effective than isolated interventions, confirming that digital capabilities should support—not substitute for—structural, operational, and strategic resilience mechanisms.

Featured Application

The proposed House of Resilience framework combined with the FHOR-RAM model provides a structured approach for analyzing resilience configurations in logistics and supply chain systems. The framework can support decision-making by helping organizations identify potential resilience weaknesses across technological, operational, structural, and strategic dimensions and explore possible improvement pathways under uncertainty. In practical applications, the assessment process can be supported by combining available organizational data sources (e.g., ERP and supplier management systems, operational performance indicators, risk registers, and expert assessments) with structured linguistic evaluations of resilience criteria. The resulting resilience profile enables decision-makers to identify critical capability gaps, prioritize improvement initiatives, and compare alternative development scenarios before implementing resilience-oriented actions. The approach is particularly applicable for resilience assessment in procurement systems, supplier risk analysis, and resilience-oriented planning. In addition, the model may support the evaluation of hypothetical development scenarios, such as improvements in digital capabilities, supplier diversification, or governance mechanisms, while recognizing that further empirical studies are required to validate its applicability across different industries and supply chain configurations.

Academic Editor: Jianhua Zhu

Received: 25 June 2026
Revised: 26 July 2026
Accepted: 28 July 2026
Published: 1 August 2026

 https://doi.org/10.3390/systems14080920

Abstract

Contemporary logistics systems operate in increasingly volatile and uncertain environments, where disruptions and digital transformation jointly shape system performance and continuity. In this context, resilience has emerged as a critical capability; however, existing approaches often remain fragmented, representing resilience either as isolated capabilities or aggregated indicators, while lacking an integrated conceptual architecture for resilience assessment. This study introduces the House of Resilience (HoR) as a hierarchical conceptual architecture that represents resilience as an emergent multi-layer system property and operationalizes this concept through the Fuzzy House of Resilience Assessment Model (FHOR-RAM). The model applies fuzzy logic with linguistic variables, triangular fuzzy numbers, and a hierarchical Mamdani-type fuzzy inference system to capture uncertainty in expert assessments and aggregate resilience measures at both layer and system levels. The proposed framework is illustrated through a real-world procurement system case study conducted in a manufacturing company operating within a global supply network. The results indicate a moderate overall resilience level (R_{HoR} = 0.402), with the weakest performance observed in the structural (R_3 = 0.31), strategic (R_4 = 0.33), and technological and risk assessment (R_1 = 0.34) layers, while the operational and adaptive layer achieved a moderate resilience level (R_2 = 0.51). The diagnostic analysis identified supplier dependency, lead-time instability, limited resilience governance, and insufficient digital capabilities as the principal resilience bottlenecks. Scenario analysis demonstrated that improvements targeting individual resilience dimensions provide only limited system-level gains, while coordinated development across multiple resilience layers enables a transition toward higher resilience levels (R_{HoR} = 0.647). The findings confirm that resilience should be addressed as a multidimensional and multi-layer system property rather than as an isolated technological capability. The study demonstrates that fuzzy inference provides an effective operational mechanism for translating the House of Resilience conceptual architecture into an interpretable and decision-oriented resilience assessment framework under uncertainty. The study demonstrates that fuzzy inference provides an effective operational mechanism for translating the House of Resilience conceptual architecture into an interpretable and decision-oriented resilience assessment framework under uncertainty. The case study illustrates how the framework can support structured resilience diagnosis and identification of potential improvement priorities within a procurement system. However, broader empirical validation, including multi-company studies and integration with organizational data sources, remains necessary to further evaluate its transferability and practical deployment potential.

Keywords: House of Resilience; logistics systems; supply chain resilience; fuzzy logic; resilience assessment; digital transformation; Industry 5.0; decision support systems; predictive analytics

1. Introduction

Contemporary logistics systems and supply chains operate in an environment characterized by increasing volatility, uncertainty, and complexity [1]. The globalization of flows, growing interdependencies within supply networks, dynamic demand fluctuations, and systemic disruptions, such as geopolitical crises, pandemics, and transportation disturbances, significantly challenge the ability of organizations to maintain operational continuity. As a result, resilience has become a critical capability in logistics and supply chain management [2–4].

In this study, these concepts are considered as related but analytically distinct levels of resilience analysis. Supply chain resilience refers to the capability of an interconnected network of organizations, including suppliers, manufacturers, logistics providers, and customers, to anticipate, absorb, recover from, and adapt to disruptions. Logistics system resilience focuses on maintaining and adapting material, information, and operational flows within such networks, whereas procurement resilience represents a functional dimension associated with supplier-related risks, sourcing continuity, and purchasing processes. Accordingly, procurement resilience should be viewed as a subsystem-level manifestation of broader supply chain resilience rather than as an equivalent concept.

Despite the growing body of literature on supply chain resilience, existing approaches remain fragmented. Resilience is often conceptualized either as a set of operational capabilities (e.g., flexibility, redundancy, responsiveness) or as a general system property, without a unified framework integrating these dimensions [2,5]. Similarly, existing resilience maturity models provide valuable mechanisms for benchmarking and monitoring resilience development; however, they commonly represent resilience through predefined capability dimensions and sequential maturity levels, offering limited explanation of how interactions among different resilience dimensions contribute to system-level resilience [6,7]. Many studies focus on isolated aspects such as risk management, inventory strategies, or disruption mitigation, while relatively limited attention is given to the development of integrated system architectures that capture the interdependencies between structural, operational, technological, and strategic elements of resilience [8–10]. These limitations are particularly relevant when resilience is analyzed across different organizational levels, as mechanisms supporting resilience at a functional level (e.g., procurement) may contribute differently to resilience at the broader logistics or supply chain level.

At the same time, the ongoing digital transformation of logistics systems, driven by technologies such as the Internet of Things, data analytics, and artificial intelligence, creates new opportunities for enhancing resilience [3,11–13]. Digital technologies enable real-time visibility, faster decision-making, and predictive capabilities, thereby supporting proactive disruption management. However, current research lacks comprehensive models that explicitly link digital capabilities with broader resilience structures in a coherent and operationalizable manner [14,15]. Therefore, the current research challenge is not only to identify individual resilience capabilities but also to develop an integrative conceptual architecture that structures how these capabilities interact and collectively contribute to system resilience.

In response to these limitations, this study addresses the following research questions:

RQ1: How can resilience in interconnected logistics systems be conceptualized as an integrated, multi-layer system architecture adaptable across different organizational levels?
RQ2: How can such an architecture be operationalized to represent interactions among resilience dimensions and enable structured assessment and decision support under uncertainty?
RQ3: What is the role of digital technologies in enhancing resilience across different system layers?

Existing resilience assessment approaches generally conceptualize resilience either as an aggregate performance indicator or as a collection of independently assessed capabilities. Although maturity models have improved the systematic evaluation of resilience development, they typically focus on describing capability levels rather than explaining the structural mechanisms through which resilience emerges from interactions among multiple system layers. Consequently, they provide limited conceptual guidance for designing coordinated resilience strategies in complex logistics systems. In contrast, the proposed House of Resilience conceptualizes resilience as a hierarchical system architecture, in which individual resilience mechanisms perform distinct functional roles and interact across multiple organizational layers. This conceptualization provides a structured theoretical perspective for analyzing resilience as an emergent system property resulting from interactions among interconnected capabilities rather than as a simple aggregation of independent indicators. Importantly, the framework is designed as an adaptable conceptual architecture, while its empirical application in this study is demonstrated within a procurement subsystem. Therefore, the case study illustrates the operational applicability of the framework at the functional level without claiming direct validation of resilience across an entire supply chain network.

To answer these questions, the main objective of this study is to develop and operationalize the House of Resilience (HoR) as a hierarchical conceptual architecture that integrates existing resilience dimensions and describes how their interactions contribute to system-level resilience. This architecture is subsequently translated into the FHOR-RAM model through a hierarchical Mamdani fuzzy inference system, enabling structured resilience assessment and supporting decision-making under uncertainty. In practical terms, the model supports a structured assessment workflow in which organizational information, operational indicators, and expert-based evaluations are transformed into a resilience profile identifying critical capability gaps and potential improvement priorities. In this context, fuzzy inference is not applied solely as a mechanism for uncertainty handling, but as a formal representation approach that captures gradual transitions, nonlinear relationships, and interdependencies among resilience dimensions.

The main contributions of the study are threefold. First, the study contributes conceptually by proposing the House of Resilience (HoR) as a hierarchical conceptual architecture that integrates individual resilience capabilities into a multi-layer representation of system-level resilience. Second, the conceptual architecture is operationalized through the Fuzzy House of Resilience Assessment Model (FHOR-RAM), which translates the conceptual HoR structure into an interpretable hierarchical fuzzy inference system. Beyond uncertainty handling, the fuzzy mechanism enables the representation of gradual transitions, nonlinear relationships, and interaction effects among resilience dimensions, supporting the assessment of resilience from a multi-layer system perspective. Third, the applicability of the proposed framework is demonstrated through a procurement case study, illustrating how the general resilience architecture can be operationalized within a specific supply chain function to support resilience diagnosis, scenario analysis, and improvement planning. The obtained resilience profile enables the identification of priority areas requiring managerial attention, while scenario analysis provides a structured mechanism for exploring possible resilience improvement pathways. The assessment process combines available organizational information with structured expert evaluations of resilience criteria, allowing the framework to be applied also in environments where complete quantitative resilience data are not available.

The remainder of the paper is structured as follows. Section 2 reviews the literature on supply chain resilience, resilience enablers, and modeling approaches. Section 3 introduces the concept of the House of Resilience (HoR) as a hierarchical conceptual architecture for representing resilience as a multi-layer system property. Section 4 presents the application of the HoR conceptual architecture in a procurement context and discusses its adaptation to logistics-related decision environments. Section 5 describes the proposed Fuzzy House of Resilience Assessment Model (FHOR-RAM), including its structure, assessment criteria, linguistic variables, and fuzzy inference mechanism. Section 6 presents the case study and demonstrates the application of the proposed model within a procurement system. Section 7 discusses the findings in relation to existing research, theoretical and managerial implications, limitations, and future research directions. Finally, Section 8 concludes the paper and suggests directions for future research.

https://doi.org/10.3390/systems14080920

2. Literature Review and Theoretical Background

Logistics systems constitute a fundamental component of the global economy, enabling the efficient flow of goods between suppliers, manufacturers, distributors, and final customers. However, the increasing complexity and global interconnectedness of supply networks significantly amplify their exposure to disruptions arising from natural disasters, technical failures, geopolitical tensions, and infrastructure constraints. In this context, resilience has emerged as a critical capability that enables logistics systems to maintain operational continuity and adapt to unexpected disturbances [16]. At the same time, contemporary supply chains increasingly strive to achieve high levels of efficiency, flexibility, and responsiveness, often resulting in highly optimized and lean operational structures [17]. While such configurations contribute to cost reduction, they also increase the vulnerability of logistics systems to disruptions in an increasingly dynamic and uncertain economic environment [18]. This tension between efficiency and resilience has become one of the central challenges in modern supply chain design, as highly optimized systems tend to lack buffering capacity and adaptive flexibility under disruption conditions. Consequently, the concepts of vulnerability and resilience have gained considerable attention over the past two decades and have become important research topics within the supply chain management literature [19,20]. Despite the growing volume of research, the literature remains fragmented across multiple streams, including risk management, operational flexibility, redundancy strategies, and digital transformation. Existing studies frequently identify resilience dimensions and capabilities but provide limited explanation of how these elements interact and contribute to resilience at the organizational or supply chain level. Similarly, quantitative modeling approaches often evaluate selected resilience aspects without being embedded within broader conceptual architectures. Consequently, there is a need for integrated frameworks that not only assess resilience capabilities but also explain their structural relationships and support operational decision-making under uncertainty.

Conceptual clarification of resilience levels is necessary because the terms supply chain resilience, logistics system resilience, and procurement resilience refer to related but distinct analytical perspectives. Supply chain resilience represents the broadest perspective, referring to the capability of the entire network of interconnected organizations, including suppliers, manufacturers, logistics service providers, and customers, to anticipate, absorb, adapt to, and recover from disruptions [21,22]. Logistics system resilience represents a more specific system-level perspective focused on the continuity and adaptability of material, information, and resource flows enabled by logistics processes, infrastructure, technologies, and coordination mechanisms. Procurement resilience constitutes a functional perspective within logistics and supply systems, concentrating on the ability of sourcing activities to maintain supply continuity through supplier management, risk identification, information integration, and adaptive decision-making.

Accordingly, this study distinguishes between the theoretical scope and empirical application of resilience analysis. The proposed House of Resilience (HoR) conceptual architecture is developed at the level of logistics system resilience, aiming to represent the interaction of structural, operational, technological, and strategic mechanisms that contribute to system-level resilience. Procurement is used as an application domain to demonstrate how these resilience mechanisms can be identified and assessed within a specific organizational function. Therefore, the empirical case study does not redefine the framework as a procurement resilience model, but rather illustrates its applicability in a procurement context.

https://doi.org/10.3390/systems14080920

2.1. Resilience in Supply and Logistics Systems

Within the broader field of supply chain resilience research, disruptions are generally understood as events that interrupt the normal functioning of interconnected supply networks, affecting material flows, information exchange, financial processes, or operational performance [22]. However, from the perspective of logistics systems, disruptions should also be considered in relation to the continuity of physical flows, infrastructure availability, information visibility, and coordination mechanisms that enable system operation. Consequently, resilience analysis requires consideration of both network-level dependencies and functional capabilities of specific logistics subsystems. For analytical purposes, supply chain disruptions can be broadly classified into three categories: natural disasters, accidental events (such as technical faults or operational failures), and intentional attacks [23]. Each category is characterized by different mechanisms of occurrence and therefore requires distinct approaches for estimating its likelihood and potential impact. However, this traditional classification is increasingly challenged by hybrid and cascading disruptions (e.g., cyber-physical failures), which combine elements from multiple categories and propagate across interconnected systems, thereby complicating risk assessment and resilience planning.

The dynamics of such events can be described using the so-called disruption profile, which illustrates changes in system performance before, during, and after the occurrence of a disruption [23]. The dynamics of the system response depend on the nature of the disruption and, according to the literature, can be described through eight phases [23], which are presented in Figure 1:

- *Preparation*. In some situations, organizations are able to anticipate potential disruptions and implement preventive measures that mitigate their impact. Such actions may include maintaining safety stocks, developing contingency plans, or establishing alternative sourcing strategies.
- *Disruptive Event*. This phase corresponds to the occurrence of the disruptive incident, which may result from natural hazards, operational failures, labor conflicts, or supplier bankruptcy. The event triggers disturbances that propagate through the supply chain network.
- *First Response*. The initial response focuses on stabilizing the situation and limiting further damage. In supply chains, this phase involves emergency operational adjustments, communication among stakeholders, and coordination of immediate mitigation actions.
- *Initial Impact*. The first operational consequences of the disruption begin to appear. Depending on the magnitude of the disturbance, the level of redundancy, and the inherent resilience of the system, the deterioration of performance may occur immediately or with some delay.
- *Full Impact*. At this stage, the disruption reaches its maximum operational effect. System performance indicators, such as production levels, material availability, and customer service performance, may decline significantly.
- *Recovery Preparation*. Activities aimed at restoring system functionality are initiated. These actions may include activating alternative suppliers, reallocating resources, or adjusting logistics and production plans.
- *Recovery*. The system gradually restores its operational capacity. Organizations may increase resource utilization, implement overtime, or mobilize additional supply chain partners to compensate for lost production or delivery capacity.
- *Long-Term Impact*. Even after operational recovery, disruptions may generate long-term consequences, particularly when customer relationships, supplier partnerships, or market reputation have been negatively affected.

Supply chain disruptions may originate from different sources, including natural hazards, accidental failures, and intentional disruptions such as cyberattacks or sabotage [23]. These disruption categories differ substantially with respect to predictability and risk estimation approaches. Natural hazards can often be analyzed using probabilistic models based on historical data, whereas accidental failures typically represent low-probability but high-impact events influenced by human and organizational factors. Intentional disruptions are particularly difficult to assess due to the adaptive behavior of adversaries. This diversity of disruption types further complicates the development of universal resilience models, as different categories require distinct analytical and managerial approaches.

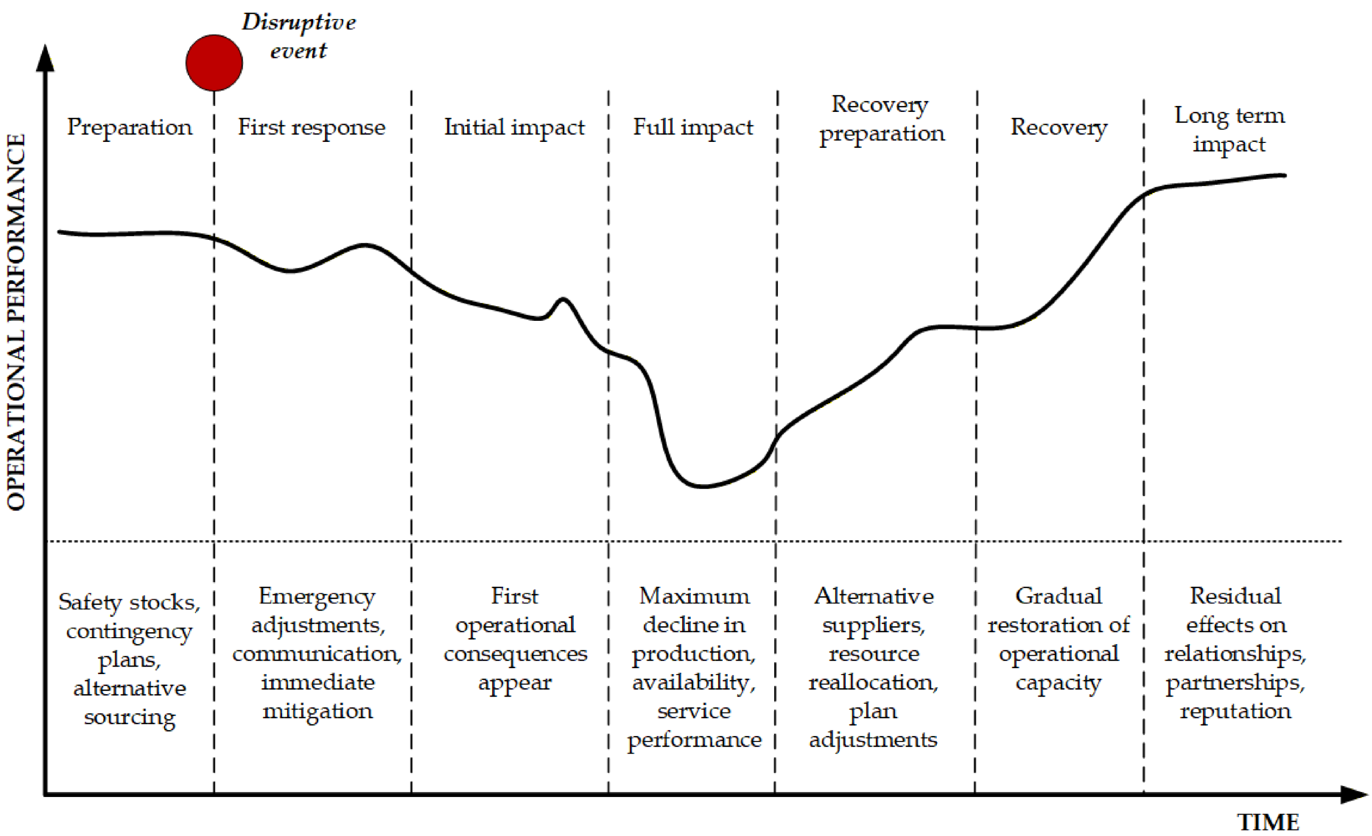

Figure 1. The dynamics of the system response. Source: own elaboration based on [24].

Operational uncertainty in logistics processes is frequently analyzed in relation to deviations from the classical “7R” logistics principle, which assumes that logistics systems should deliver the right product, in the right quantity and quality, to the right place, at the right time, for the right customer, and at the right cost [25]. Disruptions may therefore affect multiple dimensions of logistics system performance, including time, quantity, location, quality, and cost. As a consequence, such disturbances often lead to a deterioration of key performance indicators, such as production output, service levels, profitability, or customer satisfaction, before recovery mechanisms are activated [26].

Importantly, not every disruption results in system failure. The ability of logistics systems to tolerate disturbances depends strongly on the availability of time redundancy, which allows the system to absorb temporary disruptions without significantly affecting its operational objectives [27,28]. Systems equipped with sufficient temporal buffers may therefore maintain operational continuity while corrective actions are implemented. However, excessive redundancy may lead to inefficiencies and increased operational costs, highlighting the need for balanced design approaches that integrate efficiency and resilience considerations.

Within this context, supply chain resilience is commonly defined as the capability of a supply chain to withstand disruptions without significantly compromising its ability to fulfill its operational mission [29]. Although the term supply chain resilience is frequently used as the dominant concept in the literature, the mechanisms through which resilience emerges may differ depending on the analyzed system level. At the network level, resilience is primarily associated with inter-organizational relationships, diversification, redundancy, and collaboration. At the logistics system level, resilience additionally depends on operational flexibility, information visibility, technological capabilities, and adaptive process management. At the functional level, such as procurement, resilience is reflected through specific managerial practices, including supplier risk management, sourcing flexibility, and data-supported decision-making.

As resilience has been studied across multiple research domains, definitions differ not only in their conceptual emphasis but also in the level of analysis to which they are applied. Table 1, therefore, summarizes representative definitions according to their underlying system level, highlighting the transition from general system resilience concepts toward supply chain and logistics-oriented perspectives.

Table 1. Representative definitions of resilience across different system levels and their relevance to logistics systems.

Author (Year) Ref.	Domain	System Level	Definition Focus (Shortened)	Key Dimension	Perspective	Limitation
Holling (1973) [30]	Socio-ecological systems	General system level	Ability to absorb disturbance and maintain system relationships	Absorption, stability	Broad	Limited operationalization for technical/logistics systems
Bruneau et al. (2003) [31]	Community/infrastructure	Infrastructure/system level	Ability to mitigate, withstand, and recover from disasters	Resistance, recovery	Both	Focus on extreme events, less on operational continuity
Woods (2006) [32]	Engineering systems	Technical system level	Ability to recognize, adapt, and respond to unexpected disturbances	Adaptation, anticipation	Broad	High-level conceptual, limited measurable criteria
Sutcliffe & Vogus (2007) [33]	Organizational	Organizational level	Ability to maintain positive adjustment and emerge strengthened	Adaptation, learning	Predictive	Strong behavioural focus, limited system-level structure
Ponomarov & Holcomb (2009) [22]	Supply chain	Supply chain network level	Capability to prepare for, respond to, and recover from disruptions	Preparedness, response, recovery	Both	Limited integration with technological enablers
Hollnagel (2010) [34]	Safety/resilience engineering	System level (socio-technical systems)	Ability to adjust functioning before, during, and after disturbances	Adaptation, continuity	Both	Abstract; requires operationalization

Table 1. *Cont.*

Author (Year) Ref.	Domain	System Level	Definition Focus (Shortened)	Key Dimension	Perspective	Limitation
Hosseini Shekarabi et al. (2025) [10]	Infrastructure systems	Infrastructure/ system level	Ability to withstand and recover within an acceptable time and cost	Robustness, recovery	Both	Focus on performance metrics, less on adaptability
Linkov et al. (2013) [35]	Systems/ infrastructure	System level	Ability to prepare, absorb, recover, and adapt to disruptions	Full resilience cycle	Both	Generic framework, limited domain-specific detail
Hosseini et al. (2016) [36]	Supply chain	Supply chain network level	Ability to reduce disruption probability and recover performance	Risk + recovery	Both	Emphasis on risk, less on system architecture
Yarveisy et al. (2020) [37]	General systems	System level	Ability to absorb, operate in degraded mode, and recover	Absorption, recovery	Retrospective	Limited emphasis on proactive capabilities

The reviewed definitions indicate a clear evolution of the resilience concept from a focus on stability and recovery ("bounce back") toward more dynamic perspectives emphasizing adaptation, learning, and system transformation ("bounce forward"). However, despite this conceptual advancement, most definitions remain either domain-specific or highly abstract, lacking structured representations that integrate multiple system layers. In particular, limited attention is given to the role of digital technologies and their interaction with operational and strategic dimensions of resilience. This gap highlights the need for integrated, multi-layer frameworks capable of structuring interactions among resilience mechanisms across different system levels.

2.2. Strategies and Enablers of Logistics Resilience

Building resilience in logistics systems requires the coordinated application of multiple strategic, operational, and technological mechanisms. The literature increasingly emphasizes that isolated resilience measures are insufficient, and that effective resilience building requires system-level integration across multiple dimensions of logistics system design and management. These approaches focus not only on mitigating risks but also on enhancing the ability of logistics systems to anticipate, absorb, and adapt to disturbances. However, despite the identification of numerous resilience strategies, existing studies often analyze them in isolation, without explicitly addressing their interdependencies or their role within a coherent system architecture. This limitation reduces their applicability in complex, real-world logistics systems. In this context, several key resilience enablers can be identified, reflecting different dimensions of logistics system design and management. Among the most commonly discussed strategies for building resilience in the literature are the following [38–41]:

1. *Risk identification and assessment* constitute a fundamental prerequisite for resilience building. Effective resilience management requires a comprehensive understanding of potential vulnerabilities within the logistics network, including geographic exposure, geopolitical conditions, natural hazards, supply dependencies, and regulatory constraints. Systematic risk assessment enables organizations to identify critical points of failure, prioritize mitigation actions, and allocate resources in a targeted manner. Nevertheless, traditional risk assessment approaches are often static and probability-

based, which limits their applicability in highly dynamic and uncertain environments characterized by low-probability, high-impact disruptions.

2. *Supplier and transportation diversification* represents a widely recognized strategy for reducing disruption exposure. Supply chains relying on single sourcing or limited transport options are particularly vulnerable to localized disturbances. The adoption of multi-sourcing strategies and alternative transportation routes reduces dependency on individual nodes and enhances system flexibility. However, diversification may increase operational complexity and costs, and without proper coordination mechanisms, it can introduce new inefficiencies and risks.
3. *Inventory optimization* plays a critical role in balancing efficiency and resilience. While just-in-time strategies minimize inventory-related costs, they simultaneously reduce buffering capacity during disruptions. Consequently, resilient logistics systems increasingly incorporate safety stocks, strategic reserves, and dynamic inventory policies. This highlights a fundamental trade-off between efficiency and resilience, which remains insufficiently addressed in existing models that typically optimize for one objective while neglecting the other.
4. *Technology integration* significantly enhances resilience capabilities by enabling real-time monitoring, data-driven decision-making, and process automation. Technologies such as the Internet of Things, blockchain, artificial intelligence, and predictive analytics improve supply chain visibility and support early detection of disruptions. Despite their growing importance, digital technologies are often treated as isolated enablers rather than as integrated elements of resilience architectures. Moreover, digitalization may introduce new vulnerabilities related to cybersecurity, data quality, interoperability, and technological dependence. Therefore, its contribution to resilience depends on appropriate governance and integration with organizational capabilities. At the same time, digital technologies may also introduce new sources of vulnerability. Increased dependence on interconnected information systems, cloud services, automated decision support, and digital communication may expose logistics systems to cybersecurity threats, data quality problems, system failures, interoperability issues, or algorithmic errors. Consequently, digitalization should not be viewed as an inherently resilience-enhancing capability, but rather as an enabler whose contribution depends on the robustness, reliability, and governance of the underlying digital infrastructure.
5. *Collaboration and information sharing* among supply chain stakeholders are critical for coordinated disruption management. Effective communication and data exchange between suppliers, manufacturers, logistics providers, and institutional actors enable faster response and more efficient recovery processes. However, collaboration is frequently constrained by issues such as data ownership, trust, and lack of interoperability between systems, which limit its practical implementation.
6. *Supply chain visibility and transparency* are essential for enhancing responsiveness and decision-making under uncertainty. End-to-end visibility enables real-time tracking of material flows and early identification of bottlenecks. While visibility is widely recognized as a key enabler, its effectiveness depends strongly on the quality of data integration and the analytical capabilities available within the system.
7. *Resilience planning and workforce development* constitute an important organizational dimension of resilience. The implementation of contingency planning, scenario-based simulations, and structured training programs enhances preparedness and supports effective response to disruptions. Nevertheless, human and organizational factors remain underrepresented in many quantitative resilience models, which tend to focus primarily on technical and structural aspects.

8. *Sustainable logistics design* represents a cross-cutting dimension that influences the long-term effectiveness of resilience strategies. Sustainability integrates environmental, social, and economic considerations into logistics decision-making and emphasizes resource efficiency, responsible sourcing, reduced environmental impact, and long-term value creation [42,43]. From a resilience perspective, sustainable practices contribute to reducing resource dependencies, improving system adaptability, and strengthening long-term continuity under changing environmental and market conditions [40]. However, sustainability should not be considered as an isolated resilience capability. Instead, it interacts with structural, operational, technological, and strategic resilience mechanisms by shaping how these capabilities are developed and maintained over time.

The reviewed resilience enablers demonstrate that resilience should not be understood as a collection of isolated organizational capabilities but rather as a multidimensional system property emerging from the interaction of complementary resilience mechanisms. However, existing studies differ considerably in terminology, analytical perspective, and level of abstraction. Some emphasize network design and redundancy, others focus on organizational adaptability, while more recent studies highlight the role of digital technologies or strategic governance. Consequently, resilience is frequently represented as a set of heterogeneous capabilities rather than as a coherent system architecture explaining how these capabilities jointly contribute to system-level resilience.

In addition, recent studies increasingly emphasize that resilience should not be considered solely as the ability to withstand disruptions, but also as a strategic capability contributing to organizational performance and long-term sustainability. In digitally transformed logistics systems, resilience capabilities enabled by data visibility, advanced analytics, and interconnected technologies contribute to improved operational efficiency, service continuity, and adaptive decision-making [44,45]. Furthermore, the integration of sustainability-oriented strategies with digital transformation and resilience capabilities enables organizations to achieve balanced economic, environmental, and social outcomes [46,47]. Therefore, resilience can be interpreted not only as a defensive capability for disruption management but also as a strategic enabler supporting sustainable organizational performance.

A closer synthesis of the literature indicates that the identified resilience enablers can be grouped according to their primary functional role within the resilience process rather than according to their disciplinary origin. First, a substantial body of supply chain resilience research identifies supplier diversification, inventory buffering, redundancy, alternative sourcing, and network configuration as the primary mechanisms that enable systems to absorb disruptions and maintain continuity of material flows [21,26,48]. Although these mechanisms are described using different terminology across studies, they all contribute to increasing the structural robustness of supply networks by reducing dependency on individual resources and enhancing the system's capacity to withstand disruptions. Consequently, these mechanisms constitute the structural foundation of resilience.

Second, resilience engineering and organizational resilience literature emphasize adaptive response, operational flexibility, learning, monitoring, and workforce preparedness as the capabilities that determine how effectively organizations respond once disruptions occur [32,34,49]. Rather than preventing disruptions, these mechanisms enable organizations to adjust their operations, coordinate recovery activities, and continuously improve resilience capabilities through organizational learning. Collectively, they represent the operational and adaptive dimension of resilience.

Third, the rapidly expanding literature on digital supply chains identifies visibility, sensing, real-time monitoring, predictive analytics, artificial intelligence, and information integration as the principal mechanisms supporting anticipation and risk awareness [50,51].

Importantly, digital technologies do not create resilience directly. Rather, they provide enabling capabilities that strengthen an organization's ability to detect disruptions, assess evolving risks, and support timely decision-making. At the same time, digitalization may also increase system exposure to cyberattacks, data inconsistencies, software failures, algorithmic bias, and technological dependencies. Consequently, the contribution of digitalization to resilience depends not only on the deployment of digital technologies themselves but also on their secure, reliable, and well-governed implementation. Accordingly, these mechanisms form the technological and risk assessment dimension of resilience.

Finally, another stream of resilience research highlights the importance of governance, strategic planning, collaboration, resilience-oriented policies, and long-term organizational development [49,52]. These mechanisms coordinate resilience activities across organizational boundaries, align resilience objectives with business strategy, and support long-term capability development. Consequently, they constitute the strategic dimension of resilience.

The synthesis presented above suggests that the selection of these four dimensions is not based on the frequency with which individual resilience enablers appear in the literature, but rather on their distinct functional roles within the resilience process. Structural mechanisms provide the physical basis for disruption absorption, operational mechanisms determine adaptive response, technological mechanisms enable anticipation and risk awareness, whereas strategic mechanisms coordinate long-term resilience development. Together, these complementary functions explain how resilience emerges as a system-level property rather than as a set of independent organizational capabilities.

This functional synthesis also provides the theoretical rationale for the conceptual architecture proposed in this study. Although existing studies consistently recognize these resilience mechanisms, they rarely organize them into a unified hierarchical framework explaining how different resilience functions interact across organizational levels. Most approaches continue to analyze resilience enablers individually or through additive capability lists, without explicitly representing their functional interdependencies. This limitation motivates the development of the House of Resilience (HoR), in which resilience is conceptualized as an integrated four-layer architecture composed of technological and risk assessment, operational and adaptive, structural, and strategic resilience layers. Importantly, although these mechanisms are identified across supply chain, logistics, and organizational resilience literature, the proposed framework does not attempt to model the entire supply chain network structure. Instead, it focuses on logistics systems as an intermediate level of analysis, where technological, operational, structural, and strategic mechanisms interact to determine the resilience of logistics-related activities. Within this architecture, the technological layer should therefore be interpreted as an enabling layer rather than as resilience itself. It provides the information-processing and sensing capabilities upon which the remaining resilience layers operate.

The resulting functional classification of resilience enablers is summarized in Table 2, which served as the theoretical basis for defining the four layers of the proposed House of Resilience framework.

Overall, the reviewed strategies indicate that resilience should be understood not as a collection of independent capabilities, but as an emergent system property resulting from interactions among structural, operational, technological, strategic, and sustainability-related mechanisms. Structural mechanisms, including redundancy, diversification, and buffering capacity, provide the foundation for maintaining continuity. Operational and adaptive mechanisms determine the ability of logistics systems to respond and adjust under disruption conditions. Technological and risk-assessment mechanisms support visibility, anticipation, and informed decision-making, while strategic mechanisms enable long-term governance and transformation. Sustainability represents a transversal principle influencing all these dimensions by ensuring that resilience-building decisions remain environmentally responsible, socially viable, and economically sustainable over time.

Table 2. Key resilience enablers in logistics systems and their limitations.

Resilience Enabler	Primary Contribution to Logistics System Resilience	Theoretical Role	Assigned HoR Layer
Risk identification and assessment	Anticipation	Supports risk awareness and proactive decision-making	Technological and risk assessment
Technology integration (IoT, AI, analytics)	Visibility and sensing	Enables monitoring, prediction, and information integration	Technological and risk assessment
Supply chain visibility and transparency	Situational awareness	Supports early disruption detection and response coordination	Technological and risk assessment
Workforce development and resilience planning	Adaptation	Strengthens operational flexibility, learning, and recovery capability	Operational and adaptive
Collaboration and information sharing	Operational coordination	Facilitates coordinated response across supply chain actors	Operational and adaptive/Strategic
Supplier and transportation diversification	Robustness	Reduces dependency and improves disruption absorption	Structural
Inventory optimization and buffering	Absorption capacity	Provides redundancy and continuity during disruptions	Structural
Sustainable logistics design and resilience governance	Long-term resilience development	Supports strategic alignment, resource sustainability, and resilience governance	Strategic (with cross-layer influence)

Although existing studies increasingly recognize the relationship between resilience and sustainability, these concepts are often investigated through partially separated research streams. Consequently, limited attention has been given to frameworks that explain how sustainability considerations interact with different resilience mechanisms within a unified system architecture. This limitation further supports the need for an integrated framework capable of representing resilience as a multi-layer construct while acknowledging sustainability as a cross-layer design principle. This functional classification provides the theoretical foundation for the House of Resilience framework proposed in the following section.

2.3. Modeling Approaches for Supply Chain Resilience

In parallel with conceptual research, supply chain resilience has been widely investigated through quantitative modeling approaches aimed at analyzing disruption dynamics and evaluating resilience strategies. Logistics system resilience modeling typically involves the application of mathematical models, simulation techniques, and analytical frameworks that capture the complex interactions and uncertainties inherent in supply networks.

It should be noted that resilience modeling approaches differ depending on the level of analysis considered. While supply chain resilience refers to the capability of interconnected networks, logistics system resilience focuses on the continuity and adaptability of logistics processes within a defined system boundary. Procurement resilience represents a functional perspective related to sourcing continuity and supplier-related risks. Therefore, procurement resilience is considered in this study as an application domain rather than an independent resilience level. Similarly, digital resilience should not be interpreted as an independent system level, but rather as an enabling capability that strengthens visibility, anticipation, coordination, and decision-making across different resilience layers.

Despite the rapid development of modeling approaches, there is still no consensus on a unified modeling paradigm capable of capturing both the structural and dynamic aspects of resilience in logistics systems. Existing approaches often focus on selected dimensions of resilience, while providing a limited explanation of how technological, operational, structural, and strategic capabilities interact within a unified system perspective. This limitation is particularly evident in resilience maturity models, where assessment is commonly structured around predefined capability levels rather than around the structural relationships among resilience dimensions [6,53]. Several review studies summarize the evolution of this research field. For example, the authors in [54] analyzed nearly 150 publications addressing supply chain disruptions in the operations research and management science literature. Other studies review optimization-based approaches to supply chain resilience [55], quantitative resilience modeling techniques [56], sustainability-related resilience modeling [57], and resilience modeling in transportation systems [58,59]. Additional reviews focus on resilience in small and medium-sized enterprises [60] and complex engineering systems [61]. These reviews collectively indicate a growing methodological diversity; however, they also highlight fragmentation across modeling approaches and limited integration between different analytical paradigms.

Among the most frequently applied modeling approaches are agent-based modeling (ABM), discrete-event simulation (DES), system dynamics modeling (SDM), and optimization-based methods. Agent-based modeling enables the simulation of interactions among supply chain actors and allows researchers to analyze the propagation of disruptions and emergent system behaviors [62–65]. Its strength lies in capturing decentralized decision-making and heterogeneity of agents; however, ABM models are often computationally intensive and require detailed parameterization, which limits their applicability in large-scale industrial settings.

Discrete-event simulation provides a detailed representation of logistics processes and allows the evaluation of operational scenarios such as production scheduling, transportation routing, or inventory management [66,67]. While DES offers high granularity and process-level accuracy, it is typically limited to operational analysis and does not explicitly capture strategic or structural dimensions of resilience.

System dynamics modeling focuses on feedback loops and nonlinear interactions within supply chain systems, providing insights into long-term system stability and resilience [68–70]. However, SDM models often rely on aggregated representations of systems, which may oversimplify operational details and limit their applicability in decision-making at the tactical level.

Optimization models, including linear and integer programming approaches, are commonly applied to identify resource allocation strategies that balance efficiency with resilience objectives [71–74]. These approaches are effective in identifying optimal solutions under predefined constraints, but they typically assume deterministic or simplified uncertainty structures, which may not adequately reflect real-world disruption dynamics.

In addition to the above approaches, recent studies increasingly explore data-driven and machine learning methods for resilience assessment and prediction. While these approaches enable advanced pattern recognition and predictive capabilities, they often require large datasets and may lack interpretability, which limits their transparency in decision-support contexts.

These modeling approaches support a wide range of applications, including risk identification and mitigation, decision support through scenario analysis, and continuous system improvement through iterative learning processes. Within this context, resilience engineering emphasizes the design of systems capable of absorbing disturbances and adapting to unexpected events rather than attempting to eliminate all sources of risk [75–77]. Designing flexible logistics networks characterized by supplier diversification, redundant transport routes, and adaptive decision-making structures is therefore considered a key principle of resilient system design [78–80]. However, despite these advances, existing modeling approaches exhibit several common limitations: (i) they typically focus on single modeling paradigms without integrating multiple perspectives, (ii) they rarely capture the interdependencies between structural, operational, technological, and strategic dimensions of resilience, and (iii) they often lack mechanisms for handling uncertainty in expert-based assessments in a transparent and interpretable manner.

Furthermore, limited attention is given to frameworks that combine conceptual system architectures with formalized assessment models, which restricts the practical applicability of resilience modeling in decision-making processes.

In this context, it is also worth noting that several structured modeling concepts based on "house-type" representations have been successfully applied in engineering and management, such as the House of Quality (see e.g., [81–83]), the Toyota Production System House (see e.g., [84,85]), and the House of Risk (see e.g., [86–88]). These approaches provide intuitive visualization of relationships between system components and support structured decision-making. However, their application in the context of resilience remains limited, particularly with respect to integrating multiple system layers and enabling quantitative assessment under uncertainty. This observation motivates the exploration of extended frameworks, such as the House of Resilience proposed in this study.

To provide a structured comparison of the main modeling approaches discussed in the literature, Table 3 summarizes their key characteristics, strengths, and limitations, as well as the main research gaps associated with each method.

Table 3. Comparison of modeling approaches for supply chain resilience.

Method	Approach Description	Ex. Refs.	Strengths	Limitations	Limitation Relevant to the Research Problem Addressed
Agent-Based Modeling (ABM)	Simulation approach representing supply chain entities (e.g., suppliers, manufacturers, distributors) as autonomous agents interacting within a system	[62–65]	Enables modeling of decentralized decision-making and heterogeneous actors; captures interaction effects and emergent system behavior; useful for analyzing disruption propagation	High computational complexity; requires detailed parameterization and calibration; difficult to validate and scale for large systems	Limited integration with strategic decision layers and formal system architectures; rarely linked with multi-criteria assessment frameworks
Discrete-Event Simulation (DES)	Process-oriented simulation method representing logistics operations as sequences of discrete events over time (e.g., production, transport, inventory flows)	[66,67]	High level of detail in representing operational processes; supports scenario analysis and performance evaluation; widely applicable in logistics and production systems	Primarily focused on the operational level; limited representation of strategic and structural aspects; model development can be time-consuming	Limited representation of interactions across multiple resilience layers (strategic, technological); limited ability to incorporate qualitative or expert-based inputs

Table 3. *Cont.*

Method	Approach Description	Ex. Refs.	Strengths	Limitations	Limitation Relevant to the Research Problem Addressed
System Dynamics Modeling (SDM)	Aggregate modelling approach focusing on feedback loops, delays, and nonlinear relationships within complex systems	[68–70]	Effective in analyzing long-term system behavior and feedback effects; supports understanding of system stability and policy impact; suitable for strategic analysis	Uses aggregated variables, reducing granularity; may oversimplify operational details; limited applicability for detailed decision-making	Insufficient representation of micro-level processes and operational decision-making; limited integration with real-time data and technological enablers
Optimization-based models (e.g., Linear Programming, Mixed-Integer Programming)	Mathematical programming approaches used to determine optimal decisions under constraints (e.g., network design, inventory, routing)	[71–74]	Provides optimal or near-optimal solutions; supports resource allocation and trade-off analysis; well-established in operations research	Often assumes deterministic or simplified uncertainty; limited ability to model dynamic and adaptive behaviors; sensitive to model assumptions	Weak representation of uncertainty and disruption dynamics; limited integration with behavioral and adaptive system properties
Machine Learning (ML) and data-driven approaches	Data-driven methods that learn patterns from historical data to support prediction, classification, and anomaly detection	[56,57,60]	Strong predictive capabilities; effective in identifying hidden patterns and early signals of disruptions; supports real-time decision-making	Requires large datasets; limited interpretability ("black-box" models); results depend on data quality; may lack causal explanation	Limited transparency and interpretability for decision-makers; weak integration with conceptual system models and resilience architectures
House-type frameworks (e.g., House of Quality, House of Risk, Toyota Production System House)	Structured, matrix-based approaches representing relationships between system elements (e.g., requirements, risks, processes) in a hierarchical "house" architecture	[81–88]	Intuitive visualization of complex relationships; supports multi-criteria decision-making; facilitates integration of qualitative and quantitative factors; adaptable to different domains	Primarily static representations; limited ability to model dynamic system behavior; often lack formalized uncertainty handling; usually domain-specific	Lack of dynamic modeling capabilities and integration with formal analytical methods; limited application to multi-layer resilience system design under uncertainty

2.4. Research Gap

Despite the growing body of literature addressing supply chain, logistics system, and functional subsystem resilience, several conceptual and methodological gaps remain regarding the integration of existing resilience capabilities into coherent architectural representations. Existing studies typically focus either on definitional aspects of resilience, on specific managerial strategies for disruption mitigation, or on analytical modeling techniques used to evaluate resilience performance. While these research streams provide valuable insights, they often remain fragmented and rarely offer integrated perspectives on resilience system design.

First, from a conceptual perspective, the literature provides limited examples of frameworks that represent resilience as a multi-layer system architecture. However, many existing frameworks do not explicitly distinguish whether identified resilience capabilities refer to the entire supply chain network, a specific logistics system, or a functional subsystem such as procurement. As shown in Sections 2.1 and 2.2, resilience is variously interpreted as robustness, flexibility, adaptability, or recovery capability, and is operationalized through diverse enablers such as diversification, redundancy, collaboration, or digitalization. However, these elements are typically analyzed in isolation, without an explicit structure that organizes their functional roles and relationships across different resilience dimensions, including technological, operational, structural, and strategic aspects. As a result, existing approaches provide limited support for holistic system design and cross-layer decision-making. Furthermore, existing resilience maturity models, although valuable for benchmarking organizational capabilities and monitoring improvement trajectories, often conceptualize resilience as a set of independent dimensions assessed against predefined maturity levels. Such approaches implicitly assume that resilience can be represented as an additive progression of capabilities, while providing a limited explanation of how individual resilience dimensions interact and jointly contribute to system-level resilience. Consequently, maturity models may indicate the current state of resilience development but do not fully explain the underlying structural mechanisms through which resilience emerges within complex logistics systems.

Second, from a methodological perspective, current modeling approaches do not fully address the multi-dimensional and uncertain nature of resilience. As discussed in Section 2.3, simulation-based, optimization, and data-driven methods offer valuable analytical capabilities but tend to focus on selected aspects of system behavior (e.g., process dynamics, resource allocation, or prediction). These models are rarely integrated with conceptual architectures and often lack transparent mechanisms for incorporating expert knowledge and linguistic assessments under uncertainty. Consequently, their applicability in practical decision-support contexts remains constrained.

Third, although digital technologies are increasingly recognized as key enablers of resilience, their role is insufficiently integrated within existing frameworks. Current studies frequently treat technologies such as IoT, artificial intelligence, or data analytics as standalone tools rather than as components of a broader resilience architecture. This limits the understanding of how technological capabilities interact with organizational processes, operational decisions, and strategic planning in shaping system resilience.

Fourth, limited attention has been given to approaches that combine qualitative and quantitative perspectives in a consistent manner. In particular, there is a lack of models that simultaneously (i) structure resilience in terms of system architecture, (ii) enable multi-criteria evaluation across layers, and (iii) handle uncertainty inherent in expert-based assessments.

In this study, the proposed House of Resilience is positioned at the level of logistics system resilience. The framework is intended to represent resilience mechanisms that operate within a defined logistics system boundary while acknowledging that such mechanisms influence and are influenced by broader supply chain relationships. Therefore, HoR does not aim to replace supply chain resilience concepts but rather provides an architectural representation of how resilience capabilities can be structured and assessed within a logistics system context. The procurement case study represents an application of the framework within one functional subsystem of a logistics system.

The selection of the four resilience layers was not arbitrary but resulted from the synthesis of the literature presented in Sections 2.1–2.3. The reviewed studies consistently identify resilience mechanisms operating at different functional levels of logistics systems. Some mechanisms primarily enhance technological visibility and risk awareness (e.g., monitoring, predictive analytics, system integration), others improve operational adaptability (e.g., workforce flexibility, analytical capability, coordination), while another group strengthens the structural robustness of the supply network (e.g., supplier diversification, inventory buffering, lead time stability). Finally, resilience also depends on strategic governance mechanisms, including planning, collaboration, and resilience-oriented management. These four categories, therefore, represent functionally distinct but complementary resilience capabilities that jointly determine system-level resilience.

In response to these gaps, this study introduces the House of Resilience (HoR) concept as a conceptual architectural framework for organizing and integrating existing resilience capabilities into a coherent multi-layer representation. Unlike conventional maturity models that primarily organize resilience capabilities along sequential development levels, HoR provides a complementary architectural perspective in which technological, operational, structural, and strategic resilience mechanisms are organized according to their functional roles and relationships within a system.

Compared with existing approaches, the contribution of the proposed framework lies in: (i) integrating dispersed resilience enablers into a coherent architectural structure, rather than introducing new resilience dimensions; (ii) linking conceptual representation with a formalized assessment mechanism; and (iii) explicitly positioning digital capabilities as cross-layer enablers within a resilience architecture. Importantly, the objective of HoR is not to introduce new resilience mechanisms but to provide a structured representation that integrates and organizes existing resilience capabilities identified in previous research. To synthesize the identified conceptual and methodological gaps and to position the contribution of this study, Table 4 presents a structured overview linking key limitations in the existing literature with the proposed research contributions.

Table 4. Identified research gaps in supply chain resilience and the contributions of this study.

Research Gap	Description of Limitation in Literature	Ex. Ref.	Consequence for Practice	Contribution of This Study
Lack of integrated resilience frameworks	Resilience is analyzed through isolated dimensions (e.g., flexibility, redundancy, risk management), without a unified system architecture capturing their interdependencies	[19,20,39–41]	Difficulty in designing coherent resilience strategies across system levels; fragmented decision-making	Development of the House of Resilience (HoR) as a multi-layer system architecture integrating structural, operational and adaptive, technological and risk assessment, and strategic dimensions
Fragmentation of modeling approaches	Existing models (simulation, optimization, ML) focus on selected aspects of system behavior and are rarely combined into unified frameworks	[54–56]	Limited ability to support holistic decision-making; lack of consistency between modeling approaches	Proposal of FHOR-RAM, integrating conceptual modeling with a formal assessment approach
Limited integration of digital technologies	Digital tools (IoT, AI, analytics) are treated as standalone enablers rather than embedded elements of resilience architecture	[57–59]	Underutilization of digital capabilities and a lack of alignment between technology and resilience objectives	Explicit inclusion of a technological layer within the HoR framework
Insufficient handling of uncertainty	Many models rely on deterministic assumptions or require large datasets, limited use of expert knowledge, and linguistic assessment	[56,60,61]	Reduced applicability in real-world contexts with incomplete or uncertain data	Application of fuzzy logic, linguistic variables, and rule-based inference for resilience assessment

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Table 4. *Cont.*

Research Gap	Description of Limitation in Literature	Ex. Ref.	Consequence for Practice	Contribution of This Study
Lack of integration between qualitative and quantitative approaches	Conceptual frameworks are often not operationalized, while quantitative models lack interpretability and structural grounding	[54–56]	Gap between theory and practice; limited usability in decision-support systems	Integration of conceptual (HoR) and quantitative (FHOR-RAM) components into a unified framework
Limited architectural integration of resilience capabilities	Existing frameworks identify multiple resilience capabilities but provide limited guidance on how these capabilities can be functionally organized within a coherent system representation	[89–92]	Limited understanding of how resilience capabilities interact and contribute to overall system resilience; may lead to fragmented improvement initiatives focused on individual capabilities rather than holistic resilience development	Proposal of the House of Resilience (HoR) as a multi-layer system architecture that organizes existing resilience capabilities into interconnected technological, operational, structural, and strategic layers

3. Concept of the House of Resilience

3.1. Theoretical Foundation of the House of Resilience Architecture

Building upon the literature synthesis presented in Section 2, this study proposes the House of Resilience (HoR) as a hierarchical conceptual architecture representing logistics system resilience as an emergent system property. The framework is positioned at the level of a defined logistics system boundary, while recognizing that logistics systems operate within broader supply chain networks and are influenced by upstream and downstream relationships. Unlike approaches that treat resilience as a collection of independent capabilities or aggregated performance indicators, the HoR framework assumes that resilience emerges from the interaction of complementary organizational functions operating at different system levels. The theoretical contribution of the HoR architecture does not lie in introducing additional resilience dimensions, as the mechanisms represented by the proposed layers have already been recognized in previous resilience research. Instead, the contribution lies in explaining how these heterogeneous mechanisms perform complementary functions within a resilience system and how their interaction generates system-level resilience. Existing approaches typically identify resilience capabilities or maturity dimensions but provide a limited explanation of the functional dependencies between sensing, adaptation, structural robustness, and strategic transformation capabilities. The HoR architecture addresses this limitation by positioning resilience mechanisms within an integrated hierarchical structure in which each layer represents a distinct function in the resilience-building process.

Following this, the conceptual foundation of the HoR architecture is based on the functional synthesis of resilience mechanisms identified in the literature. As demonstrated in Section 2, existing studies describe resilience through diverse mechanisms, including redundancy, diversification, risk assessment, digital visibility, adaptive response, collaboration, and strategic governance. However, these mechanisms represent different functional roles within the resilience process and therefore cannot be interpreted as equivalent resilience dimensions. Importantly, the HoR framework does not aim to replace the broader concept of supply chain resilience. Instead, it provides an architectural representation of how resilience mechanisms can be structured and assessed within a logistics system. In this perspective, supply chain resilience represents the broader network-level outcome emerging from interactions among multiple organizations, whereas logistics system resilience refers to the capabilities developed within a defined operational system. Procurement resilience is subsequently treated as a functional application domain representing the upstream component of logistics system resilience.

Accordingly, the proposed framework organizes resilience mechanisms into four complementary layers: technological and risk assessment, operational and adaptive resilience, structural resilience, and strategic resilience. These layers were selected based on their distinct functional contribution to resilience development rather than on the frequency of their occurrence in previous studies. Together, they represent four fundamental functions through which defined logistics systems achieve resilience: anticipation, adaptation, absorption, and long-term transformation. The first function concerns the ability to anticipate and monitor emerging disturbances. This capability is supported by digital technologies, information integration, visibility mechanisms, and systematic risk assessment. Therefore, the technological and risk assessment layer should not be interpreted as resilience itself but as the enabling layer that provides sensing, visibility, and analytical capabilities required for resilience to emerge across the remaining layers. Digital technologies enhance the system's ability to collect, integrate, and analyze information, while risk assessment transforms these data into actionable knowledge supporting anticipation and decision-making. Consequently, resilience arises not from digital technologies alone but from their interaction with operational, structural, and strategic capabilities. At the same time, increasing digitalization also introduces new forms of vulnerability, including cybersecurity threats, data quality problems, automation failures, algorithmic bias, and dependence on interconnected digital infrastructure. These risks reinforce the need to integrate technology and risk assessment within the same architectural layer.

The second function relates to the ability of the system to respond and adapt when disruptions occur. Operational flexibility, workforce capabilities, coordination mechanisms, and organizational learning enable dynamic adjustment of processes under changing conditions. These mechanisms constitute the operational and adaptive resilience layer.

The third function concerns the structural ability of the system to absorb disruptions while maintaining continuity of operations. Supplier diversification, redundancy, buffering capacity, and network configuration represent the structural foundation of resilience by reducing vulnerability to disruption propagation. In the context of the HoR framework, these mechanisms are considered within the boundary of the analyzed logistics system, while acknowledging their dependence on external supply chain relationships.

The fourth function concerns long-term resilience development through strategic alignment, governance, planning, and continuous improvement. Strategic resilience ensures that resilience capabilities are not implemented as isolated operational actions but become embedded within organizational decision-making and development processes.

Therefore, the HoR framework should be interpreted as a system architecture for analyzing resilience capabilities within a logistics system rather than as a complete representation of resilience across the entire supply chain network. The framework provides a scalable structure that can be applied at different organizational levels; however, the present study demonstrates its applicability through a procurement system case study. Accordingly, procurement resilience is considered a specific manifestation of logistics system resilience, focusing on supplier-related vulnerabilities, sourcing continuity, and purchasing-related adaptation mechanisms.

Sustainability is considered in this study as a cross-cutting perspective influencing all resilience layers rather than as an independent resilience dimension. This perspective is consistent with the growing recognition that resilient supply chains must simultaneously address environmental, social, and economic objectives to ensure long-term viability [40].

https://doi.org/10.3390/systems14080920

Environmental sustainability contributes to resilience by reducing resource dependency, improving efficiency, and supporting adaptation to resource-related disruptions. Social sustainability strengthens resilience through workforce capabilities, stakeholder collaboration, and responsible governance mechanisms. Economic sustainability ensures that resilience-enhancing actions remain feasible over time by balancing risk reduction with operational efficiency and competitiveness.

Consequently, sustainability considerations are embedded within the HoR architecture as an enabling perspective affecting each resilience layer. At the structural level, sustainability supports resource-efficient network configurations and responsible sourcing. At the operational level, it promotes efficient processes, adaptive resource utilization, and continuous improvement. At the technological level, it encourages the development of digital solutions supporting transparency, monitoring, and sustainable decision-making. At the strategic level, sustainability becomes an element of governance, long-term planning, and organizational transformation.

The theoretical justification of these layers is summarized in Table 5.

Table 5. Theoretical derivation of the House of Resilience architecture.

HoR Layer	Theoretical Foundation	Primary Resilience Function	Representative Mechanisms	Sustainability Contribution
Technological and risk assessment	Digital supply chain resilience; Industry 4.0/5.0; risk management	Anticipation, sensing, and situational awareness	Digital technologies, visibility, monitoring, predictive analytics, risk assessment	Supports environmental monitoring, resource optimization, data-driven sustainability decisions
Operational and adaptive resilience	Resilience engineering; organizational resilience	Response, adaptation, and learning	Operational flexibility, workforce capability, coordination, learning mechanisms	Supports efficient resource utilization, process improvement, and socially responsible operations
Structural resilience	Supply chain resilience; robustness and redundancy theory	Absorption of disruptions and continuity maintenance	Supplier diversification, redundancy, inventory buffering, network configuration	Promotes sustainable sourcing, reduced dependency, and balanced economic-environmental decisions
Strategic resilience	Dynamic capabilities; organizational resilience	Governance, transformation, and long-term development	Strategic planning, collaboration, sustainability, resilience governance	Integrates sustainability objectives into long-term strategy and organizational development

The proposed four-layer architecture should therefore not be interpreted as an additional classification of resilience dimensions, but rather as a structured integration of concepts already established across different research streams. The main contribution of the HoR concept lies in connecting these previously fragmented perspectives into a coherent architecture explaining how individual resilience mechanisms collectively generate overall resilience. However, resilience within the proposed framework is not considered as an ultimate objective isolated from organizational outcomes. Instead, resilience represents an enabling capability through which logistics systems maintain operational continuity, improve adaptability, and achieve sustainable performance under changing environmental conditions. Consequently, the HoR architecture assumes a sequential relationship in which resilience capabilities support operational and strategic outcomes, including improved reliability, reduced disruption-related losses, enhanced competitiveness, and long-term sustainability.

This approach is consistent with systems theory, which assumes that complex system properties emerge from interactions among interconnected elements rather than from isolated component performance. Furthermore, it reflects principles of resilience engineering, where resilient systems are characterized by their ability to anticipate, monitor, respond, and learn under uncertainty. Finally, it incorporates the cyber-socio-technical perspective, emphasizing that contemporary logistics systems emerge from interactions among technological infrastructures, organizational processes, and human actors. In addition, the distinction between HoR and established resilience perspectives is further discussed in Section 7.1.

3.2. Structure of the House of Resilience Framework

Based on the theoretical foundation described above, the House of Resilience framework represents resilience as a hierarchical architecture composed of four interconnected levers. The structure follows the metaphor of a house, where different components perform complementary functions necessary for maintaining system stability and enabling continuous adaptation.

Based on the theoretical foundations discussed above, resilience is defined in this study as the ability of a logistics system to anticipate, absorb, adapt, and recover from disruptions while maintaining operational continuity and supporting long-term system development. This definition extends beyond traditional "bounce-back" interpretations by incorporating adaptive and transformative capabilities, enabling the system not only to restore its performance but also to evolve in response to changing environmental conditions.

To represent the structural and multi-layer nature of resilience, the HoR framework adopts the "house" metaphor, which is widely used in management and engineering to model complex systems. A well-known example is the Toyota Production System (TPS), where the house structure represents the hierarchical and interdependent nature of lean principles, with the foundation ensuring stability, pillars representing operational practices, and the roof defining system objectives. Similar approaches are used in quality management (e.g., House of Quality) and risk management (e.g., House of Risk), where the house metaphor facilitates the visualization of relationships between system components.

Building on these approaches, the proposed HoR framework extends the house-type concept by introducing a multi-layer resilience architecture combined with formal assessment capabilities, addressing the limitations identified in existing literature.

A critical element of the HoR framework is the identification of resilience levers, which constitute the structural components of the model. These levers should be understood as operational mechanisms through which the four conceptual resilience layers are developed within a logistics system. Therefore, the layers define the functional architecture of resilience, whereas the levers represent specific organizational and technological capabilities enabling their implementation. Based on the literature review, seven key levers are defined: foundational (basic), operational, analytical, human capital, technological, risk assessment, and strategic. These levers are organized into three hierarchical groups:

(a) foundational levers, forming the structural basis of resilience,
(b) intermediate levers, supporting day-to-day resilience capabilities,
(c) higher-level levers, shaping long-term adaptability and strategic development.

The interactions between these levers contribute to the development of system resilience. The HoR framework is built upon two foundational layers that ensure system stability:

- **Technological lever—**represents the technological infrastructure and digital capabilities that enable information acquisition, integration, communication, and decision support across the logistics system. Rather than constituting resilience itself, this lever provides the technological foundation upon which resilience mechanisms operating in the remaining layers can function effectively. It enables process automation, connectivity, data exchange, transparency, and adaptive control across the logistics system. Through technologies such as the Internet of Things (IoT), artificial intelligence (AI), blockchain, cloud platforms, and advanced monitoring systems, this lever enhances visibility, coordination, and responsiveness, supporting operational, analytical, and collaborative resilience capabilities. However, these technologies may simultaneously increase dependence on digital infrastructure and expose the system to cyber risks, data inconsistencies, interoperability problems, or failures of automated decision-support mechanisms. Consequently, digital technologies should be understood as resilience enablers whose effectiveness depends on their secure and reliable governance,
- **Risk assessment lever—**represents the structural component responsible for identifying and evaluating system vulnerabilities. It includes the systematic identification, analysis, and assessment of disruption sources, their probabilities, impacts, and potential cascading effects.

Without systematic risk assessment, resilience-building activities remain reactive and fragmented, as organizations lack a comprehensive understanding of system vulnerabilities. At the same time, the effectiveness of risk assessment increasingly depends on technological capabilities enabling real-time data acquisition and analysis. Conversely, risk assessment provides the interpretative context necessary to transform data into actionable decision support. Thus, these two foundational layers are mutually dependent and enable the effective functioning of the remaining resilience levers. This mutual dependence also explains why technological capabilities cannot be evaluated independently from risk assessment. Within the proposed architecture, both mechanisms jointly determine the quality of information available for resilience-oriented decision-making.

The intermediate levers form the pillars of the House of Resilience, supporting the system's ability to maintain operational continuity under disruption conditions [24]:

- **Structural lever—**defines the structural configuration of the logistics system, including supplier relationships, contractual arrangements, and the robustness of material flows. It determines the system's baseline vulnerability and its ability to maintain continuity.
- **Analytical lever—**defines the system's capability to process and interpret data to support decision-making under uncertainty. It includes predictive models, simulation tools, and analytical methods that enable disruption forecasting and scenario evaluation.
- **Operational lever—**represents the system's ability to monitor, manage, and adapt operational processes in response to changing conditions. It includes dynamic resource allocation, process reconfiguration, and corrective actions supporting real-time decision-making.
- **Human capital lever—**captures the system's ability to develop and utilize workforce competencies. It includes skills development, adaptability, collaboration, and decision-making capabilities under uncertainty.

These four levers jointly create a coherent mechanism for shaping resilience at the operational level. Each lever performs a distinct yet complementary role, and their integration determines the system's ability to respond, adapt, and maintain continuity. Importantly, the effectiveness of each lever depends on the maturity of the others, and imbalances between them may significantly reduce overall system resilience.

The strategic lever, representing the roof of the house, defines the highest level of the HoR framework. It provides long-term direction, ensures alignment across all system layers, and integrates resilience into strategic decision-making. It includes resilience-oriented planning, sustainable development, innovation, and continuous adaptation to environmental, technological, and market changes. However, sustainability should not be interpreted as being limited to the strategic layer only. Similarly, digital capabilities should not be interpreted as a separate resilience domain or as an independent source of resilience. Instead, they constitute enabling mechanisms that support visibility, anticipation, coordination, and informed decision-making across all resilience layers. Their contribution to resilience, therefore, depends on how effectively they are integrated with organizational processes, structural configurations, and strategic governance. At the same time, digitalization introduces additional technological risks that require continuous monitoring and appropriate governance within the technological and risk assessment layers. Indeed, in this sense, the strategic lever acts as an integrative mechanism aligning all other levers with broader organizational objectives.

The overall structure of the HoR framework is presented in Figure 2, illustrating the relationships between the identified resilience levers and their hierarchical organization.

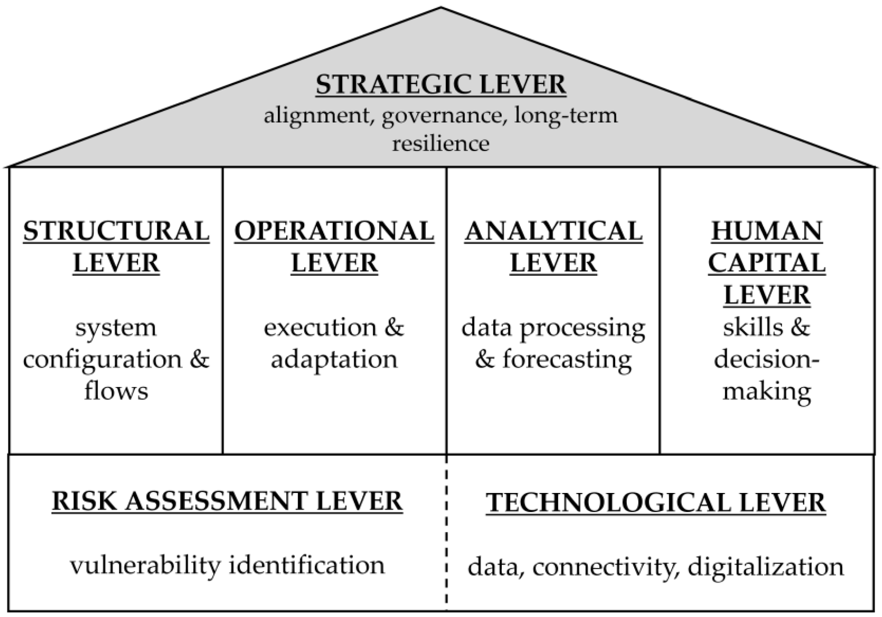

Figure 2. The House of Resilience concept for logistics systems resilience. Source: own elaboration based on [24].

4. Application of the HoR Conceptual Architecture in a Procurement Context

4.1. HoR Structure in Procurement Systems

The procurement function plays a critical role in shaping the resilience of logistics and supply systems, as it directly influences supplier selection, material availability, and risk exposure across the supply network. In increasingly volatile and digitally enabled environments, procurement must evolve from a cost-oriented function toward a resilience-oriented, data-driven, and strategically aligned process.

In this study, procurement is considered as a focal subsystem within a broader logistics system rather than as an equivalent representation of the entire supply chain. The unit of analysis of the empirical application is therefore the procurement system of a focal organization, including supplier-related processes, sourcing decisions, information flows, and procurement-related risk management mechanisms. Upstream manufacturing activities, downstream distribution networks, and external logistics service providers are outside the direct empirical scope of the case study. However, since procurement decisions influence supplier dependency, material availability, and disruption exposure, procurement resilience represents an important contributing component of broader logistics system resilience.

The House of Resilience (HoR) conceptual architecture provides a structured approach to analyzing and designing procurement processes by mapping resilience capabilities across multiple system layers. Within this context, the procurement function is conceptualized as a multi-layer system, where resilience emerges from the interaction of the four HoR layers supported by complementary resilience levers, including technological, analytical, operational, structural, human, and strategic capabilities. The application of the HoR conceptual architecture to procurement systems enables:

i identification of critical vulnerabilities within the supply base,
ii integration of real-time data and predictive capabilities into decision-making, and
iii alignment of operational activities with long-term resilience and sustainability objectives.

Importantly, the purpose of this application is not to claim that procurement resilience fully represents supply chain resilience, but rather to demonstrate how the proposed architecture can be instantiated within a specific functional area that strongly influences supply network continuity.

Figure 3 illustrates the adaptation of the general HoR architecture to the procurement subsystem. The figure illustrates procurement-related resilience mechanisms and their interactions, while recognizing that other supply chain actors may constitute additional resilience layers outside the scope of this empirical application.

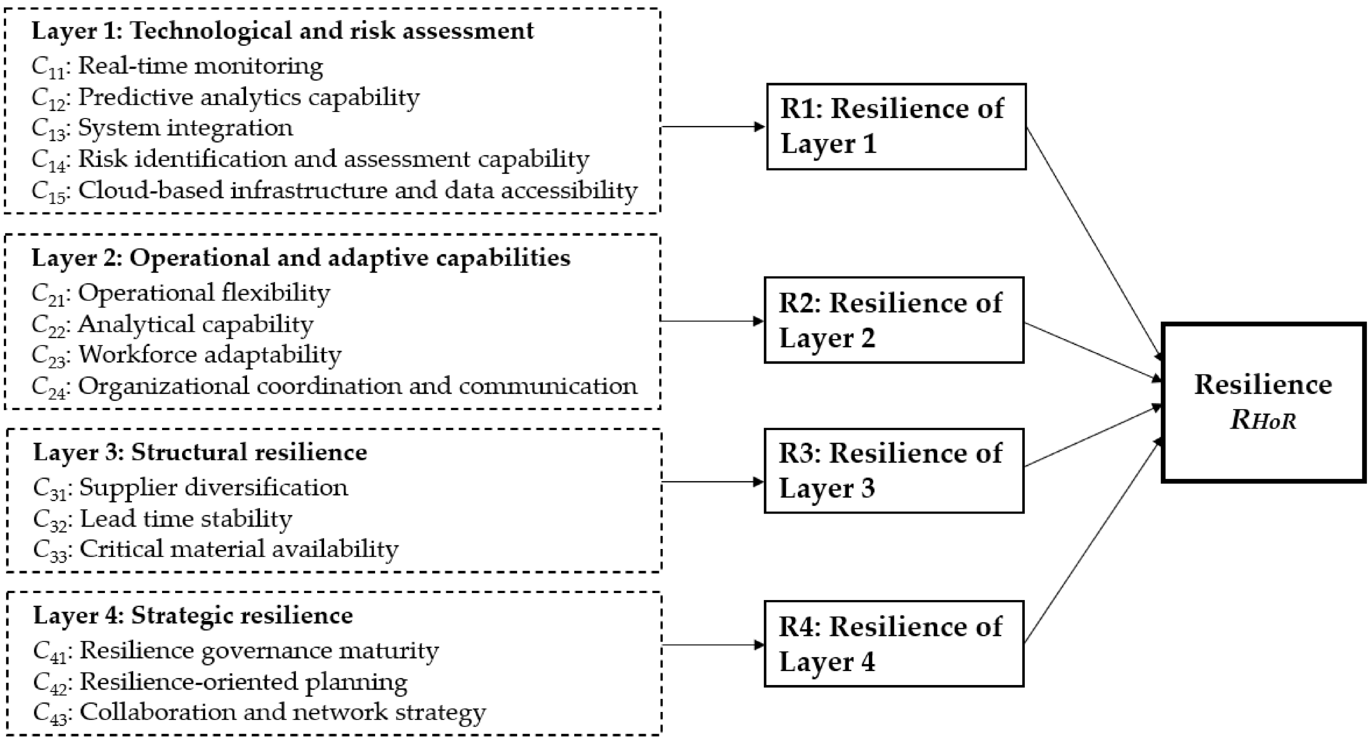

Figure 3. Application of the House of Resilience (HoR) architecture to procurement processes. Source: own elaboration.

Unlike the classical architectural interpretation of the House of Resilience, the ordering of layers in the FHOR-RAM model reflects a functional and information-processing perspective rather than a purely structural one.

In this formulation, the technological and risk assessment layer (L_1) is positioned as the entry point of the evaluation process, as it enables system visibility, data acquisition, and disruption awareness. These capabilities are prerequisites for effective operational response (L_2), structural robustness (L_3), and strategic decision-making (L_4).

Consequently, the model follows a logic of "sense–respond–structure–govern", which is consistent with resilience engineering principles and digital supply chain paradigms (Section 5).

4.2. Role of Digitalization and Risk Assessment

The effectiveness of procurement resilience is strongly determined by the interaction between the technological and risk assessment levers, which together form the enabling foundation for data-driven decision-making. At the procurement level, digital and risk-assessment capabilities primarily enhance supplier visibility and early disruption detection; their contribution to overall supply chain resilience depends on interactions with other supply chain actors and operational processes.

The technological lever represents the digital transformation of procurement processes through the implementation of technologies such as IoT, cloud computing, artificial intelligence, and blockchain. These technologies enhance procurement-related visibility, enable real-time data acquisition, and support automation and coordination across supply chain actors. In particular, digital platforms facilitate information sharing, improve transparency, and enable faster and more accurate responses to disruptions.

The risk assessment lever provides the analytical foundation for identifying and evaluating vulnerabilities within procurement systems. It includes the systematic analysis of disruption sources, probability assessment, impact evaluation, and identification of cascading effects across the supply network.

Importantly, these two levers are highly interdependent. Technological capabilities enable continuous data collection and dynamic risk monitoring, while risk assessment provides the context necessary to interpret data and support decision-making. Without this integration, procurement resilience remains reactive and fragmented rather than proactive and systematic.

4.3. Structural and System-Supporting Levers in Procurement

At the core of resilient procurement systems are the structural levers, which define the robustness of the supply base and the continuity of material flows. These include supplier diversification, lead time stability, and the availability of critical materials. At the procurement level, resilience is supported by reduced dependency on single suppliers, increased sourcing flexibility, and improved visibility of critical materials. Such capabilities enhance continuity of operations and reduce vulnerability to supply shortages, transportation delays, and market volatility. At the same time, material quality and availability considerations influence procurement resilience by affecting operational continuity.

Building upon this structural foundation, the operational, analytical, and human capital levers act as system-supporting pillars that enable the effective functioning of procurement processes under uncertainty.

The operational lever focuses on real-time monitoring and adaptive management of procurement activities, including supplier performance, inventory levels, and logistics flows. By leveraging real-time data, procurement systems can dynamically adjust sourcing decisions, reconfigure supply routes, and mitigate disruption impacts.

The analytical lever transforms data into actionable knowledge, supporting decision-making through predictive analytics, modeling, and forecasting. These capabilities enable organizations to anticipate disruptions, evaluate alternative sourcing strategies, and optimize procurement decisions under uncertainty. However, their effectiveness depends on data availability, quality, and the integration of analytical tools within existing systems.

The human capital lever reflects the importance of workforce capabilities in managing procurement resilience. It includes competencies related to decision-making under uncertainty, collaboration across supply chain partners, and the ability to effectively use digital tools. Continuous development of skills and organizational learning processes is essential to ensure adaptability in dynamic environments.

The integration of these levers ensures that procurement systems are not only structurally robust but also operationally responsive and analytically informed.

4.4. Strategic Integration of Procurement Resilience

The strategic lever represents the highest level of the HoR architecture and ensures the long-term alignment of procurement processes with organizational objectives and external environmental conditions.

Resilience-oriented procurement strategies include supplier relationship management, strategic sourcing, and sustainability-oriented decision-making. In this context, sustainability is not considered solely as an environmental objective but as an integrated mechanism supporting long-term resilience development. Sustainable procurement practices, including responsible supplier selection, resource efficiency, circular economy approaches, and consideration of social criteria, contribute to reducing vulnerability and strengthening supply continuity. Therefore, within the procurement context, resilience should not be interpreted as an ultimate objective itself, but as an enabling capability that supports organizational performance outcomes. Improved procurement resilience can contribute to reduced disruption-related losses, improved supplier reliability, more stable material availability, and better allocation of resources, which subsequently supports economic, environmental, and social sustainability objectives.

Moreover, sustainability considerations interact with all HoR layers within procurement systems. Structural resilience is enhanced through responsible supplier networks and reduced dependency on vulnerable sources. Operational resilience is supported by efficient resource utilization and continuous improvement practices. Technological resilience is strengthened through digital traceability, transparency, and sustainability-oriented analytics. Strategic resilience incorporates sustainability into governance mechanisms and long-term procurement planning. This involves not only ensuring supply continuity but also addressing environmental and social considerations, such as sustainable sourcing, resource efficiency, and circular economy practices.

Furthermore, strategic resilience requires continuous adaptation through innovation, benchmarking, and feedback-driven improvement processes. Agile and flexible strategic planning enables procurement systems to respond to evolving risks, regulatory changes, and market dynamics while maintaining long-term competitiveness.

4.5. Scope and Applicability of HoR in Procurement

The application of the HoR architecture to procurement systems provides a structured basis for both analysis and improvement of resilience capabilities. It supports organizations in identifying weaknesses across procurement-related resilience layers, evaluating alternative strategies, and designing integrated resilience-oriented procurement processes.

In addition, the HoR architecture can be operationalized through a structured sequence of resilience improvement activities, encompassing phases such as disruption response, recovery, stabilization, long-term resilience building, and continuous improvement. Furthermore, by incorporating sustainability as a cross-layer perspective, the framework supports the development of resilience strategies that are not only disruption-oriented but also aligned with long-term environmental, social, and economic objectives. This phased approach highlights the need to combine short-term responsiveness with long-term strategic development.

Importantly, the HoR architecture also creates a direct link to quantitative assessment methods by defining a clear structure of resilience dimensions and criteria. This provides the foundation for the development of formalized assessment models, such as the Fuzzy House of Resilience Assessment Model (FHOR-RAM) presented in the next section. Beyond disruption mitigation, the application of the HoR architecture supports the identification of resilience improvements that can translate into potential organizational benefits, including reduced operational losses, improved supply continuity, enhanced supplier performance, and more sustainable procurement decisions. Therefore, in this study, procurement resilience is considered both a capability for managing uncertainty within procurement processes and a contributor to broader organizational value creation.

5. Fuzzy House of Resilience Assessment Model (FHOR-RAM)

5.1. Model Overview and Conceptual Assumptions

In response to the research gap identified in Section 2.4, particularly the lack of integrated and operationalizable frameworks for resilience assessment, this study proposes the Fuzzy House of Resilience Assessment Model (FHOR-RAM). The model extends the House of Resilience (HoR) conceptual architecture (Section 3) and its application to procurement processes (Section 4) into a formalized, semi-quantitative decision-support model.

The FHOR-RAM model is designed to bridge the gap between conceptual resilience architectures and their structured assessment in logistics systems. While the HoR architecture provides a structured, multi-layer representation of resilience, it does not inherently support measurement or comparison across systems or scenarios. Therefore, the proposed model operationalizes HoR by introducing a hierarchical evaluation structure combined with fuzzy logic to address uncertainty and subjectivity in expert-based assessments.

The model is grounded in three key assumptions. First, resilience is treated as a latent, multidimensional system property, emerging from the interaction of technological and risk-assessment, operational, structural, and strategic factors. As highlighted in Section 3, resilience cannot be attributed to a single component but results from the configuration and interaction of multiple system layers.

Second, the assessment of resilience inherently involves qualitative and uncertain information, particularly in areas such as adaptability, flexibility, or decision-making capability. Consequently, fuzzy inference is employed not only to represent uncertainty associated with expert judgments, but also to model the nonlinear and context-dependent relationships between resilience dimensions. Unlike conventional additive assessment approaches, which may simplify resilience assessment by aggregating individual capabilities without explicitly representing their interactions, fuzzy inference enables the representation of conditional interactions between technological, operational, structural, and strategic factors. Therefore, fuzzy logic serves as a mechanism representing selected characteristics of resilience emergence, such as nonlinear interactions and interdependencies among resilience dimensions.

Third, resilience assessment should be context-sensitive and hierarchical, reflecting the layered architecture of the HoR model. Therefore, the FHOR-RAM adopts a multi-level structure in which resilience performance is evaluated at the level of criteria, layers, and overall system resilience. The adoption of fuzzy inference in FHOR-RAM is therefore theoretically motivated by the characteristics of resilience as an emergent system property. In complex logistics systems, a high level of one resilience capability does not necessarily compensate for deficiencies in another dimension. For example, advanced digital monitoring capabilities may not translate into effective resilience if organizational coordination or strategic preparedness is insufficient. Fuzzy inference allows such relationships to be represented through rule-based mechanisms describing how combinations of conditions contribute to different resilience outcomes.

Following this, formally, the system is defined as:

$$S = \{L,\ C,\ W,\ F\} \tag{1}$$

where

L denotes the set of resilience layers derived from the HoR structure,
C represents the set of evaluation criteria associated with individual resilience levers within each layer,
W is the vector of weights reflecting the relative importance of layers or criteria,
F defines the fuzzy membership functions used for linguistic assessment.

The model operates in three main stages:

(i) definition of criteria and linguistic variables,
(ii) fuzzy representation of resilience interactions and aggregation,
(iii) defuzzification and interpretation of results.

Importantly, the FHOR-RAM model is not intended as a purely computational tool, but rather as a decision-support framework that enables:

- identification of weak points in the resilience structure,
- comparison of resilience profiles under different assessment scenarios,
- evaluation of improvement directions in procurement and logistics systems.

As a result, it provides a theoretical–operational bridge between the conceptualization of resilience as an emergent system property and its practical evaluation. In practical applications, the FHOR-RAM model follows a structured assessment procedure in which input values for individual resilience criteria are obtained from organizational data sources and expert evaluations. Depending on the availability of quantitative information, the assessment may integrate operational indicators (e.g., supplier performance measures, delivery reliability, lead-time variability, digital capability indicators) with qualitative expert judgments related to organizational capabilities, governance mechanisms, and adaptive potential. Therefore, the model is designed to accommodate heterogeneous information sources typically available in logistics and procurement environments.

5.2. Structure of the HoR-Based Resilience Model

The FHOR-RAM model adopts a hierarchical structure directly derived from the House of Resilience concept (Section 3), ensuring full conceptual consistency between the theoretical framework and its operationalization. The model reflects the layered architecture of HoR, capturing the interactions between technological, operational, structural, and strategic dimensions of resilience.

The set of resilience layers is defined as:

$$L = \{L_1,\ L_2,\ L_3,\ L_4\} \tag{2}$$

where

L_1—Technological and risk assessment layer (digital integration and system awareness),
L_2—Operational and adaptive capabilities layer,
L_3—Structural resilience layer (structural robustness of supply and materials),
L_4—Strategic resilience layer (long-term coordination and resilience governance).

This structure reflects the HoR architecture presented in Section 3 and its application to procurement systems (Section 4), where resilience is built progressively from structural stability to strategic adaptability.

Taking one step further, each layer is represented by a set of criteria:

$$L_j = \{C_{j1}, C_{j2}, \ldots, C_{jn}\} \quad \text{and} \quad j = \{1, 2, 3, 4\} \tag{3}$$

where n represents the number of selected evaluation criteria for the jth layer.

In the FHOR-RAM operationalization, the resilience levers defined in the HoR architecture are translated into measurable assessment criteria. Therefore, levers represent conceptual capability domains, whereas criteria represent observable attributes used for evaluation. The selection of evaluation criteria constitutes a critical step in the development of the FHOR-RAM model, as it directly influences the validity, interpretability, and applicability of the assessment results. To ensure methodological rigor and transparency, a structured multi-stage selection procedure was applied.

The procedure follows a progressive filtering approach, in which an initially broad set of potential resilience indicators is systematically reduced based on theoretical, structural, and contextual considerations. This approach ensures that the final criteria set is both theoretically grounded and aligned with the House of Resilience architecture and its application to procurement systems.

The selection process consists of three main stages:

1. Literature-based identification of potential criteria,
2. Mapping and structuring according to the HoR framework,
3. Contextual refinement for procurement processes.

As a result, the proposed criteria set is intentionally limited to a manageable number of indicators per layer to ensure interpretability and applicability in real decision-making contexts.

Step 1. Literature-based identification of resilience criteria

In the first stage, a broad set of potential resilience indicators was identified based on a structured review of the literature (Sections 2.1–2.3). The analysis included studies on supply chain resilience, risk management, digital transformation, and resilience engineering. The identified criteria reflect key dimensions frequently discussed in the literature, including:

- structural robustness (e.g., redundancy, diversification),
- operational adaptability (e.g., flexibility, responsiveness),
- analytical capability (e.g., forecasting, simulation),
- technological enablement (e.g., visibility, data integration),
- organizational and human factors (e.g., skills, collaboration),
- strategic and governance aspects (e.g., planning, risk management).

A summary of representative criteria identified in the literature is presented in Table 6.

The analysis presented in Table 6 highlights that resilience-related criteria span multiple decision levels and functional dimensions. Importantly, many criteria are interdependent and cannot be assigned to a single domain without considering their systemic role. This observation supports the need for a structured mapping of criteria into the HoR framework, which is performed in the next stage of the model development process.

Table 6. Literature-derived resilience evaluation criteria.

Dimension	Example Criteria	Description	Where to Apply (Decision Level)	HoR Layer Relevance	Key Ref.
Technological	• IoT integration • cloud platforms • blockchain • system interoperability	Digital infrastructure enabling data exchange, transparency, and system connectivity	Cross-level (all)	L_1—Technological	[55,57]
Technological (Data)	• data availability • data quality • system integration • digital maturity	Ability to collect, process, and integrate data across the supply chain	Cross-level	L_1—Technological	[57,93]
Risk-related	• risk identification • vulnerability analysis • disruption propagation analysis • risk monitoring	Ability to identify, assess, and continuously monitor risks affecting the system	Strategic/tactical	L_1—Risk assessment	[94,95]
Operational	• process flexibility • rerouting capability • capacity reallocation • lead time responsiveness	Ability to adapt operational processes dynamically in response to disruptions	Operational	L_2—Operational	[40,80]
Operational (Control)	• real-time monitoring • order tracking • inventory visibility	Continuous tracking of system state enabling fast reaction to disturbances	Operational	L_1/L_2 (interface)	[66,67]
Analytical	• demand forecasting • predictive analytics • scenario analysis • simulation modeling	Ability to anticipate disruptions and evaluate alternative decisions using data-driven tools	Tactical/strategic	L_2—Operational	[54,56]
Analytical (Decision support)	• optimization models • decision-support systems • risk-based planning tools	Structured support for selecting optimal actions under constraints and uncertainty	Tactical/strategic	L_2—Operational	[71,72]
Human (Capabilities)	• workforce skills • training • adaptability • decision-making competence	Ability of employees to respond effectively under uncertainty and changing conditions	Operational/strategic	L_2—Operational	[60,61]

https://doi.org/10.3390/systems14080920

Table 6. *Cont.*

Dimension	Example Criteria	Description	Where to Apply (Decision Level)	HoR Layer Relevance	Key Ref.
Human (Collaboration)	• communication effectiveness • cross-functional coordination • stakeholder collaboration	Ability to coordinate actions across organizational and supply chain boundaries	Tactical/strategic	L_2/L_4	[96,97]
Structural (Materials & products)	• material substitutability • product standardization • safety stock • inventory buffers	Ability to maintain production continuity through material flexibility and buffering mechanisms	Operational/ tactical	L_3—Structural	[26,98]
Structural (Supply base)	• supplier diversification • multi-sourcing • geographic dispersion • supplier redundancy	Ability to reduce dependency on single suppliers and ensure continuity of supply through alternative sourcing options	Strategic/tactical	L_3—Structura	[99,100]
Strategic	• resilience planning • strategic sourcing • long-term partnerships • diversification strategy	Long-term orientation toward resilience through planning and network design	Strategic	L_4—Strategic	[78,79]
Strategic (Governance)	• risk management maturity • policies • resilience culture • performance monitoring	Organizational structures and policies supporting resilience over time	Strategic	L_4—Strategic	[20,29]
Sustainability-related	• sustainable sourcing • resource efficiency • circular economy practices	Integration of environmental and social aspects supporting long-term resilience	Strategic	L_4—Strategic	[57,101]

Step 2. Mapping to the HoR structure

In the second stage, the identified criteria were mapped into the House of Resilience framework (Section 3). This step ensures structural consistency between the conceptual model and its operationalization. Each criterion was assigned to a specific HoR layer based on its functional role within the system (see Table 6):

- criteria associated with digital technologies and risk awareness were assigned to the technological and risk assessment layer (L_1),
- criteria reflecting operational, analytical, and human capabilities were grouped within the operational and adaptive capabilities layer (L_2),

- criteria related to supply structure and resource availability were assigned to the structural layer (L_3),
- criteria related to governance and long-term planning were mapped to the strategic layer (L_4).

Step 3. Contextual adaptation to procurement systemse

In the third stage, the criteria set was refined to reflect the specific characteristics of procurement processes, as discussed in Section 4. This step involved:

- eliminating redundant or overlapping indicators,
- selecting criteria that are measurable and relevant at the procurement level,
- ensuring coverage of key procurement functions (supplier selection, sourcing, ordering, delivery, evaluation).

This step effectively transforms a generic resilience indicator set into a domain-specific evaluation framework tailored to procurement system characteristics.

To further clarify the practical operationalization of the FHOR-RAM framework, the relationship between the defined resilience layers, example assessment criteria, potential data sources, and managerial interpretation of results is summarized in Table 7. The presented examples illustrate how the conceptual dimensions of the HoR architecture can be translated into an organizational assessment procedure by combining available quantitative information with structured expert evaluations. The indicated data sources should not be interpreted as mandatory inputs, but rather as examples of information categories that may support resilience assessment depending on organizational context, data availability, and maturity level.

The information presented in Table 7 highlights that FHOR-RAM is designed as a flexible assessment framework rather than a fixed measurement system requiring a predefined data infrastructure. In practical applications, organizations may combine quantitative operational indicators with qualitative expert assessments depending on the availability and reliability of existing information sources. The role of fuzzy inference is to integrate these heterogeneous inputs into a consistent resilience profile while preserving the uncertainty inherent in expert-based evaluations.

Consequently, the resulting resilience scores should be interpreted as diagnostic indicators supporting managerial decision-making rather than as absolute measures of organizational resilience. Layer-level results allow decision-makers to identify critical capability gaps, while the overall resilience profile provides a structured basis for prioritizing improvement initiatives across technological, operational, structural, and strategic domains.

As a result, based on the three-stage selection procedure, the final set of evaluation criteria was derived through a systematic narrowing of the initial literature-based pool. Specifically, from the broad spectrum of resilience indicators identified in Step 1 (Table 6), only those criteria were retained that simultaneously (i) exhibit strong theoretical grounding in resilience literature, (ii) ensure structural alignment with the HoR architecture (Step 2), and (iii) demonstrate direct applicability to procurement processes (Step 3).

An important assumption underlying the proposed model is the relative independence of evaluation criteria within and across layers. Excessive overlap between criteria may lead to redundancy and biased aggregation results, particularly in fuzzy inference systems. To address this issue, the selection process incorporated the following principles:

1. conceptual distinctiveness—each criterion represents a unique aspect of resilience,
2. minimal overlap—criteria with similar functional roles were merged or eliminated during Step 3,
3. cross-layer separation—criteria were assigned to layers based on their dominant functional contribution.

Although complete statistical independence cannot be guaranteed in complex socio-technical systems, the adopted approach ensures a sufficient level of discriminative power and avoids major multicollinearity effects.

The adopted filtering process resulted in a parsimonious yet representative set of criteria for each layer, preserving the multidimensional nature of resilience while ensuring model interpretability and usability. Importantly, the final selection reflects a balance between completeness and practical applicability, i.e., avoiding both oversimplification and excessive model complexity.

Table 7. Examples of data sources and managerial interpretation within the FHOR-RAM framework.

HoR Layer	Example Resilience Criteria	Potential Data Sources	Assessment Approach	Managerial Interpretation of Results
L_1—Technological and risk assessment	Real-time monitoring capability, predictive analytics capability, system integration, risk identification capability	ERP/MES/SCM system records, IT architecture documentation, digital maturity assessments, monitoring system reports, expert evaluation	Combination of available digital performance indicators and expert assessment of technological and analytical capabilities	Identification of digital capability gaps, limitations in risk visibility, and opportunities for improving anticipation and early-warning mechanisms
L_2—Operational and adaptive capabilities	Operational flexibility, analytical capability, workforce adaptability, organizational coordination	Operational performance indicators, process documentation, disruption response records, employee assessments, interviews with operational managers	Evaluation of adaptive capacity based on operational evidence and organizational knowledge	Identification of barriers limiting response speed, coordination effectiveness, and adaptive performance during disruptions
L_3—Structural resilience	Supplier diversification, lead-time stability, critical material availability	Supplier databases, procurement records, supplier performance indicators, delivery history, inventory information	Assessment based on supply continuity indicators combined with expert evaluation of structural vulnerabilities	Identification of supply dependency risks, sourcing weaknesses, and priorities for supplier network redesign or buffering strategies
L_4—Strategic resilience	Resilience governance maturity, resilience-oriented planning, collaboration and network strategy	Strategic documents, risk management procedures, contingency plans, management assessments, partner collaboration records	Evaluation of the degree to which resilience is embedded in strategic decision-making and governance processes	Identification of governance gaps, limitations in long-term preparedness, and areas requiring strategic development

Consequently, the criteria assigned to each HoR layer should not be interpreted as an exhaustive list of all possible resilience determinants, but rather as a core subset of high-impact indicators that capture the dominant mechanisms of resilience formation within procurement systems. While the conceptual architecture of the HoR framework is transferable across different organizational levels, its operationalization requires the selection of criteria that are appropriate for the analyzed logistics subsystem, industrial context, and decision level. Accordingly, the proposed set of fourteen criteria represents one theoretically grounded operationalization of the HoR framework for procurement processes rather than a universally exhaustive representation of resilience determinants across all supply chain actors.

The above-presented mapping process ensures that the final criteria set reflects the hierarchical and multi-layer nature of resilience as conceptualized in the HoR framework.

The outcome of the above procedure is a structured and reduced set of evaluation criteria assigned to each HoR layer, as presented below. Each layer-specific subset reflects a distinct dimension of resilience, corresponding to its functional role within the overall system architecture.

Layer L_1—Technological and risk assessment

This layer represents the system's ability to monitor, anticipate, and interpret disruptions using digital tools and structured risk analysis.

- C_{11}: Real-time monitoring—refers to the capability of continuously tracking supply chain operations and system states using digital tools (e.g., IoT, tracking systems), enabling immediate detection of disruptions,
- C_{12}: Predictive analytics capability—denotes the ability to anticipate future disruptions and trends using data-driven models, forecasting techniques, and advanced analytics,
- C_{13}: System integration—reflects the level of interoperability between information systems across the organization and supply chain partners, enabling seamless data exchange,
- C_{14}: Risk identification and assessment capability—captures the ability to systematically identify, evaluate, and prioritize risks using structured methodologies,
- C_{15}: Cloud-based infrastructure and data accessibility—refers to the use of cloud computing solutions enabling scalable, flexible, and real-time access to data and digital services across the supply network.

This layer reflects the increasing importance of digital transformation and risk awareness in resilience building, as highlighted in Section 2.2. Moreover, these criteria are grouped within the same layer because they jointly support the system's capability to sense, interpret, and anticipate emerging disruptions. Digital technologies provide the infrastructure for data acquisition, integration, and real-time visibility, whereas risk assessment transforms this information into actionable knowledge by identifying vulnerabilities and evaluating their potential consequences. Together, these capabilities perform the common resilience function of anticipation and situational awareness, which constitutes the first layer of the HoR architecture.

Layer L_2—Operational and adaptive capabilities layer

This layer captures the system's ability to respond and adapt dynamically to disruptions.

- C_{21}: Operational flexibility—refers to the ability to adjust operational processes (e.g., sourcing, logistics, order fulfillment) in response to disruptions, independently of the underlying analytical tools,
- C_{22}: Analytical capability—denotes the ability to support decision-making through data analysis, forecasting, and scenario evaluation, without directly representing execution capability,
- C_{23}: Workforce adaptability—captures the ability of employees to adjust to changing conditions, including skills, learning capacity, and decision-making autonomy,
- C_{24}: Organizational coordination and communication—reflects the effectiveness of information exchange, coordination mechanisms, and collaboration both internally and with external partners.

The criteria correspond directly to the pillars identified in the HoR framework and reflect the integration of operational execution, data-driven decision-making, and human competencies. This layer operationalizes the resilience engineering perspective (responding, monitoring, learning). Although operational flexibility, analytical capability, workforce adaptability, and organizational communication represent distinct organizational capabilities, they are grouped within a single layer because they collectively determine the system's adaptive response once a disruption has occurred. Analytical capability supports decision-making, operational flexibility enables implementation of corrective actions, workforce adaptability provides execution capacity under changing conditions, and communication coordinates these activities across organizational boundaries. Their combined function is therefore adaptation and coordinated response rather than isolated capability development.

Layer L_3—Structural resilience (structural robustness)

This layer reflects the ability of the procurement system to ensure continuity of supply under disruption conditions.

- C_{31}: Supplier diversification—reflects the extent to which sourcing is distributed across multiple suppliers, reducing dependency risks,
- C_{32}: Lead time stability—denotes the consistency and predictability of supply lead times under normal and disrupted conditions,
- C_{33}: Critical material availability—captures the ability to ensure continuous access to key materials necessary for operations.

These criteria are derived from literature emphasizing redundancy, flexibility, and supply security as key structural enablers of resilience. Supplier diversification reduces dependency risks, lead time stability reflects process reliability, and material availability ensures continuity of operations. In addition, these criteria are grouped together because they collectively determine the system's inherent capacity to absorb disruptions before adaptive actions become necessary. Unlike the previous layer, which focuses on dynamic response, structural resilience reflects the configuration of the procurement system itself, including supplier network design, material availability, and supply continuity. Together, these mechanisms define the baseline robustness upon which the remaining resilience layers operate.

Layer L_4—Strategic resilience

This layer captures long-term system orientation and governance mechanisms.

- C_{41}: Resilience governance maturity—reflects the degree of formalization, integration, and continuous improvement of governance structures supporting resilience, including policies, decision-making frameworks, accountability mechanisms, and integration of resilience into organizational management systems,
- C_{42}: Resilience-oriented planning—denotes the extent to which long-term planning explicitly incorporates resilience considerations, including disruption scenarios, contingency strategies, and proactive design of buffering, redundancy, and risk mitigation mechanisms across the supply chain,
- C_{43}: Collaboration and network strategy—captures the strategic alignment and depth of relationships with supply chain partners, including trust, integration, and joint resilience initiatives.

These criteria are grouped within the strategic layer because they collectively shape the long-term direction, governance, and continuous development of resilience capabilities. Rather than supporting day-to-day disruption management, they define how resilience is embedded in organizational policies, strategic planning, inter-organizational relationships, and continuous improvement processes. Consequently, this layer provides the governance mechanisms that align and coordinate the development of all other resilience layers over time. It should also be noted that, while risk-related aspects are also addressed in the technological and risk assessment layer (L_1), they refer to operational and analytical capabilities (e.g., risk identification and monitoring). In contrast, the strategic layer captures governance-level mechanisms that define how resilience is embedded in organizational structures and decision-making processes. The final set of fifteen criteria was not intended to provide an exhaustive representation of all resilience determinants identified in the literature. Instead, the selection aimed to identify a parsimonious set of high-impact criteria that simultaneously satisfied three conditions: (i) strong theoretical support across multiple resilience research streams, (ii) clear functional alignment with one of the four HoR layers, and (iii) direct applicability to procurement processes. Criteria exhibiting substantial conceptual overlap or representing indirect manifestations of resilience were intentionally excluded to preserve model interpretability and avoid redundancy.

In the final stage, the relative importance of criteria and layers may be determined using multi-criteria decision-making methods, such as the Analytic Hierarchy Process (AHP). This approach enables structured pairwise comparisons and improves the robustness of the assessment. However, in the present study, equal weighting is adopted as a baseline assumption, ensuring model simplicity and general applicability. The integration of AHP-based weighting is proposed as a direction for future research and empirical validation. However, it should be emphasized that the equal weighting adopted in the present study refers exclusively to the absence of explicit numerical importance coefficients (e.g., AHP-derived weights). It does not imply that all criteria or resilience layers exert an identical influence on the final resilience assessment. Within the proposed FHOR-RAM model, the substantive influence of individual criteria emerges from the fuzzy rule base, which captures conditional dependencies, bottleneck effects, and nonlinear interactions among resilience dimensions. Consequently, the model distinguishes between numerical weighting and rule-based influence. Whereas weighting specifies the predefined relative importance of individual criteria, the fuzzy inference mechanism determines their context-dependent contribution to resilience according to the configuration of other resilience capabilities.

The purpose of defining the set of layers L_j and associated criteria C_{ji} is to enable the formal assessment of system resilience as a multidimensional and hierarchical construct. In the proposed framework, resilience is not treated as a directly observable variable but as a latent property emerging from the combined performance of multiple interrelated system attributes.

Accordingly, the evaluation process is structured as a bottom-up aggregation mechanism, in which individual criteria are first assessed and then progressively aggregated at the layer level, ultimately leading to the overall resilience score of the system.

The above-defined criteria sets for each layer constitute the input variables of the resilience assessment model. Each criterion represents a distinct and operationalizable aspect of system performance, enabling structured evaluation using expert judgment. In a practical implementation scenario, the assessment process consists of four sequential activities. First, the organization defines the assessment scope, including the analyzed logistics subsystem, organizational level, and relevant stakeholders. Second, data and expert evaluations are collected for each resilience criterion using available operational records, digital systems, performance indicators, and structured assessment questionnaires. Third, the collected information is transformed into linguistic variables and processed through the fuzzy inference mechanism. Finally, the obtained layer-level and system-level resilience results are interpreted to identify critical weaknesses and prioritize improvement actions.

In the next step, these criteria are formalized as input variables of the aggregation model, forming the basis for both layer-level and system-level resilience evaluation.

Formally, let the evaluation of criterion C_{ji}, belonging to layer L_j, be denoted as x_{ji}, where j = 1,2,3,4 represents the layer index and i = 1, 2, . . ., n_j denotes the criteria within a given layer. At the first level of aggregation, the resilience of each layer is determined as a function of its corresponding criteria:

$$R_j = f_j(x_{j1},\ x_{j2},\ \ldots,\ x_{jn}) \tag{4}$$

where R_j represents the partial resilience score of layer L_j, and $f_j(\cdot)$ is an aggregation function reflecting the contribution of individual criteria.

At the second level, the overall system resilience is computed as an aggregation of layer-level resilience scores:

$$R_{HoR} = g(R_1,\ R_2,\ R_3,\ R_4) \quad (5)$$

where R_{HoR} denotes the overall resilience level of the system, and $g(\cdot)$ represents the aggregation operator combining structural, operational, technological, and strategic dimensions.

In the baseline formulation, both $f_j(\cdot)$ and $g(\cdot)$ may be represented using weighted averaging operators. However, weighted averaging approaches assume linear compensation among resilience dimensions, meaning that deficiencies in one dimension can be fully offset by strengths in another. Such an assumption may not reflect the behavior of complex logistics systems, where certain combinations of weaknesses may significantly reduce overall resilience. Therefore, fuzzy inference is introduced to represent nonlinear relationships and conditional dependencies among resilience layers. Through rule-based reasoning, the model captures how specific configurations of capabilities contribute to different resilience outcomes. This hierarchical aggregation structure ensures that the model captures the multi-layered nature of resilience while preserving interpretability at both the criterion and system levels. Moreover, it provides a transparent link between local system characteristics and the global resilience outcome, enabling targeted identification of weaknesses and improvement priorities.

This distinction is particularly important for interpreting the proposed model. Although all criteria and layers are initially treated with equal numerical importance, the final resilience assessment is governed by the expert-defined fuzzy rule base. Therefore, resilience does not emerge from a weighted linear aggregation but from conditional interactions among resilience dimensions. Certain resilience capabilities may become decisive under specific configurations (e.g., weak structural resilience limiting overall resilience despite strong technological capabilities), reflecting bottleneck effects rather than implicit numerical weighting.

To sum up, the proposed structure ensures that the FHOR-RAM model is not only theoretically grounded in the HoR concept but also practically applicable for resilience assessment in procurement and logistics systems. By integrating structural, operational, technological, and strategic dimensions within a unified framework, the model addresses the key limitations of existing resilience assessment approaches identified in Section 2.4.

5.3. Linguistic Variables and Membership Functions

In accordance with the hierarchical structure defined in Section 5.2, the evaluation of each criterion C_{ji} is performed using linguistic variables, reflecting the qualitative, uncertain, and context-dependent nature of resilience assessment. As resilience is a latent and multidimensional construct, many of its determinants cannot be measured directly using precise numerical data. Moreover, resilience-related capabilities often interact in a nonlinear manner, meaning that their contribution to overall system resilience depends not only on their individual levels but also on their configuration within the system. Therefore, linguistic variables and fuzzy representation are adopted not only to capture vagueness and ambiguity in expert judgments, but also to represent gradual transitions between resilience states and the context-dependent interpretation of resilience capabilities.

Accordingly, each criterion value is represented as a triangular fuzzy number (TFN):

$$\widetilde{x}_{ij} = \left(a_{ji},\ b_{ji},\ c_{ji}\right) \quad (6)$$

where $\left(a_{ji},\ b_{ji},\ c_{ji}\right) \in [0, 1]$ denote the lower, modal, and upper bounds of the fuzzy assessment of criterion C_{ji}, respectively.

The general form of the triangular membership function is [102]:

$$\mu(x) = \begin{cases} 0, & x \leq a \\ \dfrac{x-a}{b-a}, & a \leq x \leq b \\ \dfrac{c-x}{c-b}, & b \leq x \leq c \\ 0, & x \geq c \end{cases} \tag{7}$$

A unified five-level linguistic scale is adopted across all criteria to ensure consistency and comparability of expert evaluations:

$$LV = \{Very\ Low,\ Low,\ Medium,\ High,\ Very\ High\} \tag{8}$$

Each linguistic term is associated with a predefined TFN defined over the normalized interval [0, 1], as presented in Table 8.

Table 8. Linguistic scale and corresponding triangular fuzzy numbers (TFNs).

Linguistic Term	Abbreviation	TFN (a, b, c)
Very Low	VL	(0.0, 0.0, 0.2)
Low	L	(0.1, 0.3, 0.5)
Medium	M	(0.4, 0.6, 0.8)
High	H	(0.65, 0.85, 1.0)
Very High	VH	(0.85, 1.0, 1.0)

Importantly, the fuzzy representation prevents an artificial assumption of precise thresholds between resilience states, reflecting the fact that transitions between different resilience levels are gradual rather than discrete. The adoption of a normalized scale facilitates comparability across criteria and supports aggregation at both layer and system levels, as defined in Section 5.2. Moreover, the use of TFNs ensures computational simplicity while preserving the ability to model uncertainty in expert judgments. However, to ensure reproducibility and consistency of the assessment process, it is necessary to explicitly define the semantic interpretation of each linguistic term for every evaluation criterion. Without such definitions, linguistic evaluations may be interpreted differently by individual experts, leading to inconsistencies in the results. Therefore, Table 9 provides a comprehensive interpretation of all five linguistic levels (VL–VH) for each criterion included in the FHOR-RAM model.

The structured interpretation of linguistic variables presented in Table 9 ensures a consistent and transparent evaluation process, reducing subjectivity and enhancing the reliability of expert assessments. It also enables the model to be applied across different organizational contexts while maintaining comparability of results. Importantly, the fuzzy representation of criteria evaluations constitutes the input to the aggregation mechanism defined in Section 5.2. Specifically, the fuzzy values $\widetilde{x}_{ij}$ are used to compute layer-level resilience R_j, which are subsequently aggregated into the overall system resilience score R_{HoR}. Thus, the definition of linguistic variables and membership functions provides a critical link between qualitative expert knowledge and the quantitative structure of the FHOR-RAM model, enabling its application as a decision-support tool under conditions of uncertainty.

Table 9. Interpretation of linguistic variables for resilience evaluation criteria.

Criterion	Very Low (VL)	Low (L)	Medium (M)	High (H)	Very High (VH)
C_{11}: Real-time monitoring	No monitoring systems; no digital visibility; decisions based on delayed or absent information	Fragmented monitoring; delayed data; limited system coverage; lack of integration	Partial real-time visibility (selected processes monitored); limited integration	High real-time tracking across key processes; integrated dashboards; near real-time data availability	Full end-to-end visibility; real-time data across entire supply chain; fully integrated and synchronized monitoring systems
C_{12}: Predictive analytics capability	No predictive tools; no formal forecasting; decisions based on ad hoc estimates or intuition	Basic trend analysis; simple forecasting models; low predictive accuracy	Moderate predictive models; some forecasting accuracy; limited scenario analysis	Advanced predictive analytics; scenario-based forecasting; models regularly used	Fully integrated predictive and AI-based analytics; continuous learning models; automated decision support
C_{13}: System integration	Completely isolated systems; manual data exchange; no interoperability	Limited integration; some digital interfaces; significant data silos remain	Partial integration; key systems connected; moderate interoperability	High integration; most systems interoperable; consistent and reliable data exchange	Fully integrated ecosystem; seamless interoperability; real-time data synchronization across all partners
C_{14}: Risk identification and assessment	No formal risk management; risks recognized only after disruption occurs	Ad hoc or incomplete risk analysis; no structured methodology	Periodic risk identification; basic tools (e.g., risk registers)	Systematic risk assessment; structured methods applied regularly	Continuous, real-time risk monitoring; predictive risk analytics; full system awareness
C_{15}: Cloud-based infrastructure and data accessibility	No cloud solutions; data stored locally; limited accessibility and scalability	Limited cloud usage; fragmented solutions; restricted data access	Moderate cloud adoption; key systems accessible remotely; partial scalability	Advanced cloud infrastructure; high data availability; scalable and flexible systems	Fully cloud-enabled ecosystem; real-time global access; high scalability; seamless data sharing across network
C_{21}: Operational flexibility	Rigid processes; no adaptability; fixed schedules/resources; no contingency options	Limited flexibility; adjustments possible but slow, costly, and reactive	Moderate flexibility; some resource reallocation and rescheduling possible	High flexibility; dynamic adjustments possible with moderate effort	Fully agile system; real-time adaptation; automated or semi-automated reconfiguration
C_{22}: Analytical capability	No analytical tools; decisions purely reactive, experience-based or intuitive; no structured analysis	Basic descriptive analytics (reports, historical data); limited decision support	Standard forecasting (time-series, basic models); limited scenario analysis	Advanced analytics; scenario modeling; decision-support systems actively used	Fully integrated predictive and prescriptive analytics; AI-supported decision-making embedded in processes

Table 9. *Cont.*

Criterion	Very Low (VL)	Low (L)	Medium (M)	High (H)	Very High (VH)
C_{23}: **Workforce adaptability**	Low skill level; no training; resistance to change; no autonomy	Limited skills; occasional training; low adaptability	Moderate skills; basic cross-functionality; some adaptability	Highly skilled workforce; continuous training; strong adaptability	Expert-level workforce; proactive learning; high autonomy; strong resilience culture
C_{24}: **Organizational coordination and communication**	No structured communication; siloed operations; lack of information sharing internally and externally	Limited coordination; informal communication; delays in information flow	Moderate coordination; defined communication channels; partial integration with partners	Strong coordination; structured communication; efficient cross-functional collaboration	Fully integrated communication network; real-time information sharing; strong internal and external alignment
C_{31}: **Supplier diversification**	Single supplier; no alternatives; dependency > 90%; no contingency contracts	Two suppliers but high dependency (>70%); limited switching capability	3–4 suppliers; moderate diversification (no single supplier dependency); partial switching capability	Multiple suppliers (>4); geographically diversified; moderate flexibility	Fully diversified global network; no critical dependency (<30% per supplier); dynamic sourcing
C_{32}: **Lead time stability**	Lead times highly volatile (>50% deviation); unpredictable; frequent disruptions	High variability (30–50%); frequent delays; weak control	Moderate variability (15–30%); partially predictable	Low variability (<15%); mostly predictable; supported by planning systems	Highly stable (<5–10%); fully predictable; actively controlled in real time
C_{33}: **Critical material availability**	Frequent shortages; no safety stock; high disruption risk	Occasional shortages; limited buffers; reactive replenishment	Acceptable availability; safety stock exists but not optimized	High availability; proactive inventory management; rare shortages	Fully secured supply; strategic reserves; alternative materials; zero disruption risk
C_{41}: **Resilience governance maturity**	No formal governance; no policies or accountability structures related to resilience	Basic governance structures; limited formalization; reactive approach	Defined governance processes; roles and responsibilities partially assigned	Well-established governance; integrated into management systems; proactive approach	Fully mature governance system; continuous improvement; resilience embedded in organizational culture

Table 9. *Cont.*

Criterion	Very Low (VL)	Low (L)	Medium (M)	High (H)	Very High (VH)
C_{42}: Resilience-oriented planning	No resilience planning; no contingency strategies; no consideration of risk mitigation or buffering mechanisms	Basic contingency plans; limited scope; reactive approach to disruptions; minimal integration with risk analysis	Moderate planning; some scenario-based approaches; partial inclusion of risk mitigation strategies (e.g., limited buffers or alternatives)	Advanced planning; multiple disruption scenarios analyzed; systematic integration of risk mitigation strategies, including redundancy and buffering decisions	Fully integrated resilience planning; dynamic, scenario-based, continuously updated; proactive and optimized design of buffering, redundancy, and mitigation strategies across the supply network
C_{43}: Collaboration and network strategy	No collaboration; siloed operations; no partner integration	Limited coordination with key partners; low trust level	Moderate collaboration; basic information sharing	Strong partnerships; coordinated planning and decision-making	Fully integrated network; strategic alliances; shared platforms; joint resilience strategies

5.4. Fuzzy Inference and Rule Base

To operationalize the evaluation framework defined in Sections 5.2 and 5.3, a fuzzy inference system (FIS) is developed to model the relationships between resilience criteria, layer-level resilience, and the overall system resilience. In contrast to conventional assessment approaches based on linear aggregation of independent indicators, the fuzzy inference system enables representation of conditional relationships among resilience dimensions. Therefore, the FIS is used as a mechanism for translating the systemic interactions assumed in the HoR architecture into computational rules. The proposed model adopts a Mamdani-type fuzzy inference system, which is widely used in decision-support applications due to its interpretability and suitability for expert-based knowledge representation. In the context of resilience modeling, the advantage of Mamdani inference is not limited to computational handling of uncertain inputs; it enables the formal representation of qualitative causal relationships between resilience mechanisms and system-level outcomes. The Mamdani approach was selected due to its interpretability and suitability for expert-driven systems, in contrast to Sugeno models, which are more computationally efficient but less transparent. In addition, the FIS is implemented using the Fuzzy Logic Toolbox in MATLAB, ensuring computational transparency and reproducibility of results.

5.4.1. Structure of the Fuzzy Inference System

The FHOR-RAM model is structured as a two-level hierarchical fuzzy inference system:

(a) Level 1—Layer-level inference:

- Inputs: criteria C_{ji} within each layer L_j,
- Output: fuzzy resilience score of layer L_j.

(b) Level 2—System-level inference:

- Inputs: fuzzy resilience scores R_1, R_2, R_3, R_4 obtained from layers L_1, L_2, L_3, L_4,
- Output: overall resilience score R_{HoR}.

This hierarchical structure ensures:

- modular representation of resilience components,
- reduction of rule-based complexity,
- consistency with the conceptual HoR framework,
- controlled propagation of uncertainty from criteria to system-level assessment,
- representation of emergent resilience formation through progressive aggregation of interacting system layers.

5.4.2. Mamdani Inference Mechanism

The inference process follows the classical Mamdani approach and consists of four sequential stages: fuzzification, rule evaluation, aggregation, and defuzzification.

Fuzzification:

Crisp input values corresponding to the evaluation of criteria C_{ji} are transformed into fuzzy values using the triangular membership functions defined in Section 5.3. For each input x_{ij}, the degree of membership in each linguistic set $A_k \in LV$ is calculated as (based on Equation (7)):

$$\mu_{A_k}(x_{ij}) \in [0, 1] \tag{9}$$

This allows for representing uncertainty and partial belonging of inputs to multiple linguistic categories. In the context of FHOR-RAM, partial membership also reflects transitional resilience states, where a logistics system may simultaneously exhibit characteristics of different resilience levels rather than belonging exclusively to one predefined category.

Rule evaluation (implication):

Each rule is activated based on the degree of satisfaction of its antecedents. The firing strength α_r of rule r is computed using:

- the minimum operator for conjunction (AND),
- the maximum operator for disjunction (OR), if applicable:

$$\alpha_r = \min(\mu_{A_1}, \mu_{A_2}, \ldots, \mu_{A_n}) \tag{10}$$

The implication is performed by truncating the output membership function:

$$\mu^*_{B_r}(y) = \min(\alpha_r, \mu_{B_r}(y)) \tag{11}$$

Aggregation:

The outputs of all activated rules are combined using the maximum operator:

$$\mu_{out}(y) = \max_r \mu^*_{B_r}(y) \tag{12}$$

This operation ensures that all relevant rules contribute to the final fuzzy output while preserving the highest degree of membership at each point of the output domain.

Defuzzification:

In the final stage, the aggregated fuzzy output is transformed into a crisp numerical value representing the resilience level used for interpretation and comparison. The FHOR-RAM model employs the centroid (center of gravity) method, which is one of the most widely used defuzzification techniques due to its stability and interpretability. The defuzzified value R is calculated as:

$$R = \frac{\int y\mu_{out}(y)dy}{\int \mu_{out}(y)dy} \tag{13}$$

where $\mu_{out}(y)$ is the aggregated membership function; y represents the output variable.

This method computes the center of gravity of the resulting fuzzy set, providing a balanced representation of all activated rules and their respective contributions.

The described mechanism is applied both at the layer level and at the system level, ensuring consistency of inference across the entire model.

5.4.3. Rule Base Design

In the present study, the fuzzy rule base was developed by the authors as theory-informed expert knowledge. Rather than eliciting rules from a formal expert panel, the authors translated the conceptual assumptions of the HoR framework and resilience mechanisms reported in the literature into an explicit set of linguistic inference rules. Consequently, the proposed rule base should be interpreted as an initial theoretical operationalization of the HoR framework, intended to support conceptual modeling rather than as a universally validated knowledge base.

The fuzzy rule base constitutes the core of the inference system, as it encodes expert knowledge about the relationships between individual resilience criteria and the resulting resilience performance at both the layer and system levels. In this sense, the rule base does not merely represent uncertainty but formalizes theoretical assumptions regarding how resilience mechanisms interact. The IF–THEN relationships provide an explicit representation of assumed functional relationships among resilience capabilities, including reinforcing effects, limiting factors, and non-compensatory interactions.

The fuzzy rules were not derived from historical operational data or statistically learned from empirical observations. Instead, they were developed as theory-informed expert rules based on three complementary sources: (i) the conceptual assumptions of the House of Resilience framework, (ii) established resilience engineering principles reported in the literature, and (iii) domain knowledge related to procurement and supply chain resilience assessment. Therefore, the rule base should be interpreted as an explicit representation of assumed resilience relationships rather than as an empirically identified causal model.

The development process consisted of four sequential steps. First, the functional role of each resilience layer was defined within the HoR architecture. Second, qualitative relationships between criteria and resilience outcomes were identified based on literature-derived resilience mechanisms. Third, these relationships were translated into linguistic IF–THEN rules using the predefined five-level linguistic scale. Finally, the resulting rule sets were reviewed for logical consistency, monotonic behavior, and coverage of representative resilience configurations.

Beyond numerical aggregation, the rule base represents the functional relationships assumed within the HoR framework by defining how combinations of resilience capabilities contribute to emergent system behavior. In the proposed FHOR-RAM model, the rule base reflects the causal logic embedded in the House of Resilience (HoR) framework, ensuring consistency between conceptual assumptions and computational implementation.

The fuzzy rules follow a standard IF–THEN structure:

$$\text{IF } C_{ji} \text{ is } A_1 \text{ AND } C_{ji} \text{ is } A_2 \text{ AND} \ldots \text{ THEN } L_j \text{ is } B$$

where C_{ji} denotes the i-th criterion within layer L_j; A_i and $B \in LV$ are linguistic terms defined in Section 5.3.

At the system level, an analogous structure is applied:

$$\text{IF } L_1 \text{ is } A_1 \text{ AND } L_2 \text{ is } A_2 \text{ AND } L_3 \text{ is } A_3 \text{ AND } L_4 \text{ is } A_4 \text{ THEN } R_{HoR} \text{ is } B$$

This formulation enables a consistent propagation of information from criteria to layers and from layers to the overall resilience score.

The rule base is developed based on a set of methodological and domain-specific assumptions, ensuring both interpretability and logical consistency:

- Theory-informed expert reasoning—rules represent domain-informed assumptions regarding relationships between resilience capabilities and system outcomes. These assumptions are derived from resilience literature, the functional logic of the HoR architecture, and procurement resilience principles.
- Monotonicity assumption—it is assumed that improvements in input criteria should not lead to a deterioration of resilience. Formally, higher linguistic values of inputs (e.g., High, Very High) should result in equal or higher output levels.
- Dominance relationships between criteria—certain criteria may exert a stronger influence on the resulting resilience assessment under specific boundary conditions. Rather than assigning explicit numerical weights, the FHOR-RAM model captures such effects through the structure of fuzzy rules. Thus, equal weighting and dominance effects operate at two different methodological levels. Equal weighting concerns the formal importance assigned to criteria during the aggregation structure, whereas dominance relationships are implemented within the fuzzy inference rules to represent context-dependent interactions among resilience capabilities. Such influence does not represent numerical weighting but emerges from the configuration-dependent behavior of fuzzy rules. Consequently, dominance should not be interpreted as implicit weighting, but rather as a behavioral property of the inference mechanism consistent with the non-compensatory assumptions of the HoR framework. This approach reflects the assumption that resilience cannot always be explained by additive compensation mechanisms. In complex logistics systems, the simultaneous presence of weaknesses in critical dimensions may create systemic vulnerability even when other capabilities are highly developed. For example, extremely low values of critical criteria (e.g., critical material availability, resilience governance maturity, or cloud-based infrastructure accessibility) may trigger lower resilience outputs even when other criteria perform well. This approach reflects the systemic nature of resilience while maintaining the equal-weight assumption adopted at the aggregation level.
- Non-compensatory logic—the model assumes that extremely low values of critical criteria cannot be fully compensated by high values of other inputs. At the system aggregation level, this principle is additionally enforced through dedicated mixed-condition rules representing configurations with multiple low-performing layers. These rules ensure that resilience deficiencies occurring simultaneously across several dimensions of the House of Resilience architecture constrain the final resilience assessment, thereby reducing excessive compensatory effects that may arise from fuzzy interpolation.
- Consistency with HoR architecture—the rules are aligned with the layered structure of the model, ensuring that each layer reflects its intended functional role (structural, operational, technological, strategic).

The number of possible fuzzy rules increases exponentially with the number of input variables (criteria) and linguistic terms. For a system with five linguistic levels and n_j criteria within layer L_j, the theoretical number of rules is given by:

$$N_j = 5^{n_j} \tag{14}$$

Based on the structure defined in Section 5.2, the theoretical rule base size for each layer is presented in Table 10.

Table 10. Theoretical rule base size.

Layer	Number of Criteria	Theoretical Number of Rules
L_1—Technological & risk assessment	5	$5^5 = 3125$
L_2—Operational and adaptive capabilities	4	$5^4 = 625$
L_3—Structural resilience	3	$5^3 = 125$
L_4—Strategic resilience	3	$5^3 = 125$

At the system level, aggregation of the four layers would theoretically require: $5^4 = 625$ rules. Consequently, a fully enumerated rule base would result in over 4500 rules in total, which is impractical in terms of:

- interpretability,
- computational efficiency,
- expert validation and calibration.

Given the exponential growth of the rule base (Table 10), a full enumeration of all possible rule combinations is neither practical nor necessary. Therefore, a reduced rule base is constructed to capture the dominant system behavior while maintaining interpretability and computational efficiency. The reduction process follows a structured and reproducible approach.

Instead of generating all possible combinations, the rule base is defined using three categories of rules:

1. Extreme rules (boundary conditions)
   Representing the limits of system behavior:
   - all inputs Very Low—output Very Low,
   - all inputs Very High—output Very High.
2. Reference rules (balanced scenarios)
   Representing typical system states:
   - all inputs at the same level (Low, Medium, High),
   - consistent performance across criteria.
3. Dominance-based rules (mixed scenarios)
   Capturing realistic conditions where:
   - one or more criteria significantly influence the output,
   - critical weaknesses (e.g., Very Low) dominate the result,
   - majority logic applies (e.g., most inputs High—High output).

Following this, the final rule base is obtained by applying the following operational rules:

- permutation reduction: equivalent combinations of inputs are represented by a single rule (order of criteria does not matter),
- dominance assumption: critical low-performance criteria (e.g., Very Low) can determine the output regardless of other inputs,
- monotonicity constraint: increasing input levels should not decrease the output level,
- heuristic grouping: similar input configurations are aggregated using linguistic patterns (e.g., "majority High").

The reduced rule base was constructed using a transparent rule-selection protocol rather than subjective elimination of individual combinations. The protocol prioritizes representative patterns of resilience behavior instead of exhaustive enumeration of all possible input combinations. As a result of the reduction process, the number of rules is significantly decreased (Table 11).

Table 11. Reduced number of rules in the model.

Layer	Theoretical Rules	Final Rule Base
L_1—Technological & risk assessment	3125	48
L_2—Operational and adaptive capabilities	625	35
L_3—Structural resilience	125	30
L_4—Strategic resilience	125	30
System level	625	48

To assess the logical adequacy of the reduced rule base, the rules were designed to ensure coverage of all major resilience states represented by the linguistic scale. The rule set includes:

- failure scenarios,
- low-performance scenarios,
- balanced configurations,
- high-performance scenarios,
- excellence scenarios,
- mixed and transitional configurations.

Consequently, every linguistic region of the input space is represented by at least one rule, while fuzzy interpolation mechanisms ensure smooth transitions between explicitly defined rules.

The reduced rule base preserves the key nonlinear relationships between criteria while ensuring high interpretability (limited number of intuitive rules), computational efficiency, and feasibility of validation, future expert review, and calibration. From a managerial perspective, this rule-based structure enables decision-makers to understand not only the final resilience level but also the underlying configurations of capabilities that contribute to this outcome. Consequently, FHOR-RAM supports diagnostic analysis by indicating which resilience dimensions represent limiting factors and where improvement actions may generate the highest system-level benefits.

Due to the use of fuzzy membership functions, the model interpolates between defined rules, ensuring smooth output transitions across the entire input space despite the reduced rule set.

Complete rule bases for Layers L_1, L_2, L_4, as well as the full system-level aggregation rule base, are provided in Appendix A. To illustrate the implementation of the rule reduction strategy, the structural resilience layer (L_3) is selected as an example because it represents the foundational role of supply continuity within the HoR architecture. Complete rule bases are provided in Appendix A, whereas Appendix B provides a detailed illustration of the rule reduction procedure using Layer L_3.

To sum up, the methodological contribution of FHOR-RAM does not result from the standalone application of fuzzy inference, which is a well-established approach in decision-support systems. Instead, the novelty lies in integrating fuzzy reasoning with a resilience architecture that explicitly represents resilience as a layered and emergent system property. Unlike conventional fuzzy assessment models, where criteria are aggregated directly into a single performance index, FHOR-RAM introduces a hierarchical inference structure reflecting the functional dependencies between technological awareness, operational adaptability, structural robustness, and strategic governance. Therefore, fuzzy inference serves as a computational mechanism for operationalizing the theoretical assumptions of the House of Resilience rather than merely as an aggregation technique.

5.5. Results Interpretation and Model Applicability

The final output of the FHOR-RAM model is a crisp resilience score $R_{HoR} \in [0, 1]$, obtained through the hierarchical fuzzy inference process described in Section 5.4. This scalar value represents the aggregated level of resilience of the analyzed procurement system and reflects the integrated contribution of structural, operational, technological, and strategic dimensions of resilience. In contrast to single-dimensional performance indicators, the proposed score captures resilience as a latent, multi-layer system property emerging from the interaction of heterogeneous system attributes. Importantly, the role of fuzzy inference in the FHOR-RAM model extends beyond uncertainty representation. The fuzzy mechanism provides a theoretical means for modeling resilience as an emergent phenomenon characterized by nonlinear interactions, partial dependencies, and transition effects among heterogeneous system capabilities. Unlike additive assessment approaches, where resilience is assumed to result from the direct aggregation of independent indicators, fuzzy inference allows the representation of situations in which combinations of moderately developed capabilities may generate higher resilience outcomes, while critical deficiencies in specific dimensions may significantly constrain the overall system resilience.

5.5.1. Interpretation of Resilience Scores

To ensure interpretability and practical usability of the model in decision-making contexts, the resulting resilience score is mapped onto a predefined qualitative classification scale. This transformation from a continuous numerical output into discrete linguistic categories enables meaningful interpretation by decision-makers and supports comparative and diagnostic analysis.

The interpretation scale (Table 12) is constructed as a uniform partition of the normalized interval [0, 1], ensuring consistency, transparency, and symmetry of classification boundaries. The boundaries are not intended to represent empirically validated resilience thresholds but serve as interpretative categories supporting managerial communication. Each interval corresponds to a distinct resilience state characterized not only by its numerical range but also by its underlying system behavior, particularly in terms of vulnerability, adaptability, and capacity for disruption absorption and recovery.

The proposed classification provides a structured interpretation framework that translates a continuous fuzzy output into actionable managerial insights. Beyond numerical classification, the fuzzy representation preserves the gradual and context-dependent nature of resilience transitions. This is theoretically relevant because resilience development rarely follows discrete capability jumps; instead, organizations typically evolve through intermediate states where different resilience mechanisms coexist and interact. Importantly, the boundaries between categories should not be interpreted as rigid thresholds but rather as soft transitions, consistent with the fuzzy logic foundation of the FHOR-RAM model. This means that systems located near boundary values (e.g., 0.59 vs. 0.61) may exhibit overlapping characteristics of adjacent resilience levels.

This approach supports graded decision-making, where improvements in resilience are interpreted incrementally rather than as abrupt state changes. Such a representation is particularly relevant for complex socio-technical systems, where resilience evolves continuously rather than discretely.

From a decision-support perspective, the classification enables:

- diagnostic evaluation, by identifying the current resilience state of the system,
- benchmarking, by enabling comparison across systems, suppliers, or organizational units,
- temporal analysis, by tracking resilience evolution over time,
- target setting, by defining desired resilience levels for strategic planning.

Table 12. Interpretation of resilience score.

Score Range	Resilience Level	Interpretation
0.00–0.20	Very Low	The system exhibits critical vulnerability and structural fragility. Resilience-related mechanisms are either absent or severely underdeveloped. The system is highly exposed to disruptions and lacks the capability to maintain continuity of operations under stress conditions. Immediate and fundamental redesign of structural and operational components is required.
0.20–0.40	Low	The system demonstrates limited resilience, characterized by predominantly reactive behavior. Basic response mechanisms may exist; however, they are insufficient to effectively manage disruptions. Recovery is slow and costly, and the system remains dependent on external stabilization mechanisms. Significant improvements in redundancy, visibility, and coordination are necessary.
0.40–0.60	Moderate	The system achieves an acceptable but non-robust level of resilience. It indicates a high capability to maintain operational continuity under moderate disturbances; however, performance degradation occurs under severe or compound disruptions. Resilience is largely reactive rather than proactive, indicating partial development of adaptive and anticipatory capabilities.
0.60–0.80	High	The system demonstrates strong resilience with well-developed adaptive capabilities. It is able to effectively detect, respond to, and recover from disruptions with limited performance loss. Proactive mechanisms such as monitoring, forecasting, and coordination are partially or fully implemented, enabling controlled system adaptation under uncertainty.
0.80–1.00	Very High	The system is highly resilient, exhibiting advanced levels of adaptability, anticipation, and strategic alignment. Resilience is embedded across structural, operational, technological, and governance layers. The system is capable of maintaining stable performance even under severe and unexpected disruptions, while continuously improving through learning and feedback mechanisms.

Importantly, due to the hierarchical structure of the FHOR-RAM model, interpretation can be consistently performed at multiple levels of abstraction:

- criterion level, capturing local system attributes x_{ji},
- layer level, represented by partial resilience scores R_j,
- system level, represented by the overall resilience score R_{HoR}.

This multi-level interpretability constitutes one of the key advantages of the proposed framework, as it enables both global assessment and local diagnosis of resilience weaknesses within procurement systems. From a managerial perspective, the interpretation of FHOR-RAM outputs follows a diagnosis-to-action logic. The overall resilience score provides information about the general resilience condition of the analyzed system, whereas layer- and criterion-level results indicate where improvement actions should be directed. Therefore, the model does not prescribe a single optimal decision but supports prioritization of resilience-enhancing interventions, such as supplier diversification, digital capability development, operational flexibility improvement, or strengthening of resilience governance mechanisms.

5.5.2. Diagnostic Capabilities of the Model

Beyond providing a single aggregated resilience score R_{HoR}, the FHOR-RAM model enables a structured and multi-level diagnostic analysis of system resilience. Due to its hierarchical architecture and bottom-up fuzzy aggregation mechanism, the model not only quantifies resilience but also preserves information about the contribution of individual criteria and layers to the final system outcome. From a theoretical perspective, this mechanism allows resilience to be analyzed as a system configuration rather than as an isolated capability score. Therefore, fuzzy inference contributes to the operationalization of resilience theory by enabling the representation of interaction patterns between resilience dimensions and by revealing how specific combinations of strengths and weaknesses influence the overall system state. This feature is particularly important in decision-support contexts, where understanding why a system exhibits a given resilience level is as critical as the final assessment itself.

A key diagnostic capability of the model lies in the decomposition of the overall resilience score into layer-specific outputs R_1, R_2, R_3, R_4, which correspond to the technological and risk assessment layer, operational (pillar) layer, structural layer, and strategic layer, respectively. This decomposition enables the identification of asymmetries in resilience development across different functional domains of the procurement system.

In particular, the FHOR-RAM model supports the identification of three core diagnostic patterns:

(1) Weak layer identification

The model allows for direct detection of structurally weak resilience components. A significantly lower value of a specific layer score (e.g., R_3) indicates a bottleneck in the corresponding subsystem. For instance, low performance in the structural layer suggests vulnerabilities related to supplier base robustness, material availability, or lead time stability, which may critically affect system continuity even if other layers demonstrate satisfactory performance.

(2) Cross-layer imbalance detection

The hierarchical structure of the model enables the identification of disproportionate development between resilience dimensions. A typical case involves high technological capability (e.g., high R_1) combined with weak structural resilience (low R_3), or strong operational performance (high R_2) without corresponding strategic alignment (low R_4). Such imbalances indicate that resilience is not systemically embedded but rather concentrated in isolated dimensions, increasing the risk of systemic failure under complex disruptions. This capability differentiates FHOR-RAM from additive resilience indices, where compensatory effects may hide critical weaknesses.

(3) Criterion-level sensitivity and criticality analysis

Due to the fuzzy rule-based aggregation mechanism, the model preserves traceability from system-level output to individual criteria C_{ji}. This allows identification of critical drivers of reduced resilience, particularly those criteria whose low linguistic evaluations (e.g., *Low* or *Very Low*) propagate through the inference system and noticeably reduce layer-level outputs. Examples include supplier diversification, critical material availability, or resilience governance maturity, which may act as structural bottlenecks within the system.

From an interpretative perspective, the diagnostic logic of the model can be summarized through typical decision-relevant patterns:

- A low value of R_3 indicates structural fragility, often associated with supplier dependency, insufficient buffering capacity, or limited material availability.
- A low value of R_1 reflects insufficient technological and risk awareness capabilities, such as weak monitoring systems, limited data integration, or inadequate predictive analytics.
- A mismatch between R_2 and R_4 (e.g., strong operational performance but weak strategic resilience) indicates operationally efficient but strategically misaligned systems, where short-term adaptability is not supported by long-term governance mechanisms.

Importantly, the FHOR-RAM model enables not only the identification of weaknesses but also their structural localization within the resilience architecture, allowing decision-makers to distinguish whether observed deficiencies originate from technological limitations, operational constraints, structural vulnerabilities, or governance deficiencies.

This diagnostic capability represents a key advantage of the proposed approach compared to traditional resilience assessment methods, which typically focus on aggregated indices without providing explanatory insight. In contrast, the FHOR-RAM model supports a diagnosis-to-intervention pathway, enabling targeted improvement actions such as strengthening supplier networks, enhancing digital integration, improving workforce adaptability, or reinforcing resilience governance mechanisms.

Consequently, the model transforms resilience assessment from a purely evaluative procedure into a prescriptive decision-support tool, capable of guiding resilience enhancement strategies in procurement and supply chain systems.

5.5.3. Scenario Analysis and Decision Support

The FHOR-RAM model is inherently designed to support scenario-based analysis, enabling systematic evaluation of alternative system configurations, policy choices, and strategic interventions within procurement systems. Due to its fuzzy logic foundation and hierarchical structure, the model allows decision-makers to explore not only a single static assessment of resilience, but also the resilient response of the system to changes in key input conditions.

In this context, scenario analysis is implemented by modifying selected input variables x_{ji} at the criterion level, either in linguistic or crisp form, and observing their propagated effects on layer-level resilience scores R_j and the overall system resilience R_{HoR}. This bottom-up propagation mechanism enables explicit tracing of how localized changes influence system-wide resilience outcomes.

A key feature of the proposed model is its ability to support what-if analysis, which allows decision-makers to evaluate the impact of hypothetical improvements or deteriorations in specific resilience components. Such scenario-based reasoning represents an extension of traditional resilience assessment approaches, which usually evaluate resilience as a static level. Through fuzzy inference, the FHOR-RAM model enables exploration of nonlinear resilience responses, where identical improvements in individual capabilities may lead to different system-level effects depending on the existing configuration of other resilience layers. For example, increasing supplier diversification (C_{31}), improving predictive analytics capability (C_{12}), or enhancing resilience governance maturity (C_{41}) can be directly translated into updated fuzzy inputs, resulting in recalculated resilience scores. This enables structured evaluation of improvement strategies before their actual implementation.

Beyond standard what-if analysis, the FHOR-RAM model supports sensitivity-oriented reasoning, enabling identification of criteria with potentially strong influence within the fuzzy rule structure. Due to the fuzzy rule-based aggregation mechanism, small changes in critical inputs, particularly those associated with structural or governance layers, may lead to non-linear changes in layer-level and system-level outputs. This property enables decision-makers to identify sensitivity hotspots, i.e., criteria that exert disproportionate influence on overall resilience. Such information is particularly valuable for prioritization of improvement actions under resource constraints.

The model further enables decision path analysis, where alternative strategic interventions can be compared in terms of their expected impact on resilience evolution. Instead of evaluating isolated changes, decision-makers can construct and compare multiple improvement trajectories, such as:

- technology-driven pathway (strengthening L_1 through digitalization and analytics),
- structure-driven pathway (enhancing L_3 via supplier diversification and buffering),
- governance-driven pathway (reinforcing L_4 through planning and policy integration),
- balanced resilience development strategy across all layers.

This capability is particularly relevant in procurement systems, where resilience improvements are typically constrained by budget, time, and organizational capacity. The FHOR-RAM model allows explicit comparison of trade-offs between competing investment priorities, such as digital transformation versus workforce development or operational flexibility versus supply base diversification.

Importantly, the scenario analysis framework is not limited to deterministic evaluation but is consistent with the fuzzy logic structure of the model. This means that uncertainty in input assessments is preserved throughout the analysis, allowing decision-makers to evaluate the robustness of outcomes under imprecise or incomplete information. As a result, scenario outputs should be interpreted as resilience ranges or tendencies, rather than fixed deterministic values.

From a managerial perspective, the scenario-based functionality of the FHOR-RAM model supports three key decision-making objectives:

- ex-ante evaluation, enabling assessment of planned interventions before implementation,
- comparative analysis, supporting selection among alternative procurement strategies,
- robustness assessment, identifying solutions that maintain acceptable resilience under varying conditions.

Consequently, the model functions not only as a diagnostic tool but also as a prescriptive decision-support system, enabling proactive resilience design in procurement and supply chain systems operating under uncertainty.

5.5.4. Practical Applicability in Procurement Systems

The FHOR-RAM model is designed as a decision-support framework for resilience-oriented procurement management across a wide range of organizational contexts. Its primary objective is to bridge the gap between conceptual resilience models and operational decision-making tools applicable in real procurement environments characterized by uncertainty, incomplete data, and heterogeneous information sources.

A key strength of the proposed approach lies in its ability to integrate both qualitative expert knowledge and limited quantitative data within a unified fuzzy inference structure. Unlike purely data-driven models that require large historical datasets or machine learning calibration, the FHOR-RAM framework operates effectively under conditions of data scarcity, making it particularly suitable for real-world procurement systems where complete datasets are often unavailable or fragmented across organizational units and supply chain partners.

From a methodological perspective, the model is conceptually compatible with digital twin and expert-based environments, where procurement managers, logistics specialists, and supply chain analysts provide linguistic assessments of system performance. These assessments are directly translated into fuzzy inputs, enabling structured yet flexible evaluation without requiring precise numerical measurements. This feature significantly reduces implementation barriers in practice.

The modular architecture of the model, aligned with the House of Resilience (HoR) structure, ensures direct compatibility with core procurement functions, including supplier selection, sourcing strategy design, order management, and delivery performance monitoring. Each resilience layer (L_1–L_4) can be interpreted as a distinct analytical module, enabling partial or full adoption of the model depending on organizational maturity and available data infrastructure.

Importantly, the FHOR-RAM model demonstrates strong potential for integration with digital decision-support systems (DSS). Due to its rule-based structure and explicit input–output mapping, the model can be embedded into procurement analytics platforms as an interpretative layer supporting managerial decision-making. This enables automated or semi-automated resilience assessment within existing procurement information systems (e.g., ERP or supply chain management platforms), enhancing situational awareness and supporting evidence-based decisions.

Furthermore, the model is conceptually compatible with digital twin environments, particularly in the context of supply chain and procurement digitalization. Within a digital twin framework, real-time or periodically updated system data can be mapped onto the FHOR-RAM structure to continuously evaluate resilience levels under evolving operational conditions. This enables dynamic monitoring of procurement resilience and supports proactive identification of emerging vulnerabilities.

From an applicability perspective, the model is suitable for both large-scale industrial systems and small and medium-sized enterprises (SMEs). In the case of SMEs, where data availability and analytical resources are typically limited, the low data requirement and reliance on expert judgment represent a significant advantage. The model enables SMEs to perform structured resilience assessments without the need for advanced infrastructure, advanced analytics teams, or high-frequency data collection systems.

The FHOR-RAM framework can be applied across multiple organizational and sectoral contexts, including:

- manufacturing companies with complex supplier networks,
- logistics service providers operating in dynamic environments,
- procurement coordination units managing multi-tier supply chains,
- public procurement systems requiring transparency and risk awareness.

Typical application scenarios include:

- structured resilience assessment and auditing of procurement systems,
- evaluation and benchmarking of supplier network robustness,
- support for digital transformation initiatives in procurement and logistics,
- integration of sustainability objectives with resilience-oriented decision-making,
- assessment of procurement system readiness for disruption-prone environments.

From an implementation perspective, the application of FHOR-RAM can be organized as a structured managerial assessment process consisting of four main steps. First, the organization defines the assessment scope by identifying the analyzed logistics subsystem, organizational level, and relevant resilience objectives. Second, input information for individual resilience criteria is collected from available organizational sources, including operational records, supplier performance data, enterprise information systems, risk assessment reports, strategic documents, and structured expert evaluations. Third, the collected information is transformed into linguistic assessments and processed through the fuzzy inference mechanism to obtain criterion-, layer-, and system-level resilience outputs. Finally, the results are interpreted to identify resilience bottlenecks and prioritize improvement actions. This procedure enables the model to be applied even in situations where complete quantitative datasets are unavailable, as qualitative managerial knowledge can be incorporated through the fuzzy assessment mechanism.

Overall, the practical value of the FHOR-RAM model lies in its ability to transform abstract resilience concepts into a structured and adaptable decision-support framework that can be progressively implemented within organizational resilience assessment processes. By combining fuzzy logic, hierarchical system representation, and expert-driven evaluation, the model provides a scalable framework that can be adapted to different levels of organizational maturity and digital readiness.

To sum up, the FHOR-RAM model provides a complete and operationalized framework for resilience assessment in procurement systems, integrating hierarchical system decomposition, fuzzy logic-based evaluation, and multi-level interpretability. The proposed structure enables not only the quantification of resilience at the system level, but also its decomposition into interpretable layer- and criterion-level insights, thereby supporting both diagnostic and decision-support functions. In addition, the model demonstrates strong applicability in scenario-based analysis and practical procurement environments characterized by uncertainty and limited data availability. By combining theoretical consistency with computational implementability, the FHOR-RAM framework establishes a structured bridge between conceptual resilience models and real-world decision-making needs in procurement and supply chain systems. Therefore, the main methodological contribution of the FHOR-RAM is not the use of fuzzy logic itself, but the integration of fuzzy reasoning with a theoretically grounded resilience architecture that preserves the hierarchical and emergent nature of resilience while enabling operational assessment and decision support.

As a result, in the following section, the proposed model is applied to a real-world case study in order to demonstrate its practical applicability, demonstrate its interpretative capabilities, and illustrate its usefulness in evaluating procurement system resilience under realistic operational conditions.

6. Case Study

The purpose of the case study is not to provide comprehensive empirical validation of the proposed FHOR-RAM model, but rather to demonstrate its applicability and illustrate how the conceptual HoR architecture can be operationalized in a real procurement context. Indeed, the case study focuses on demonstrating three main functionalities of the FHOR-RAM model: (i) transformation of heterogeneous procurement information into structured resilience assessments, (ii) identification of resilience strengths and bottlenecks at layer and criterion levels, and (iii) evaluation of the overall resilience state using the hierarchical fuzzy inference mechanism.

The practical implementation of FHOR-RAM followed a structured assessment procedure. First, the organizational scope of the analysis was defined as the procurement subsystem responsible for supplier management, sourcing continuity, and material availability. Second, the selected resilience criteria were evaluated using linguistic variables corresponding to the FHOR-RAM input scale. Third, the obtained assessments were processed through the hierarchical fuzzy inference mechanism to calculate criterion-level, layer-level, and overall resilience scores. Finally, the results were interpreted from a managerial perspective by identifying resilience bottlenecks and defining potential improvement directions.

6.1. Case Study Context and System Description

The analyzed case study concerns a company operating in the pneumatic components industry, engaged in both the production of pneumatic systems and the distribution of complementary finished goods. The procurement system under investigation is characterized by a dual sourcing structure, comprising (i) procurement of finished commercial products and (ii) procurement of raw materials and components used in manufacturing processes. This configuration makes the system representative of hybrid procurement environments combining production-oriented and trading-oriented supply flows.

From a supply base perspective, finished goods are predominantly sourced from European suppliers, mainly located in France and Germany. For most product categories, the company operates with a limited supplier base, typically involving one or two suppliers per product group, with deliveries organized in regular and stable replenishment cycles. In contrast, production materials are sourced globally, with suppliers located both in Europe and China, introducing higher exposure to geographical and logistical variability. Although supplier redundancy is limited for selected categories, the organization maintains partial flexibility through alternative sourcing options for specific material groups.

The procurement and logistics processes are supported by an integrated digital infrastructure. Purchasing activities are managed within an Enterprise Resource Planning (ERP) system, while warehouse operations are coordinated through a Warehouse Management System (WMS) fully integrated with the ERP environment. Additionally, a Business Intelligence (BI) system is used for operational reporting and analytical purposes. For more advanced analyses, the IT department develops dedicated spreadsheet-based tools, which rely on data exported from the ERP system. Due to system performance constraints, data extraction is performed exclusively during off-peak hours, typically at night, which introduces a temporal delay in analytical availability and limits real-time decision support capabilities.

The warehouse system is highly automated, with approximately 75% of material handling operations executed using an Automated Storage and Retrieval System (AS/RS). The remaining processes are carried out in conventional warehouse zones using pallet trucks and manual handling. Product and material identification is based on barcode technology, enabling standardized and automated tracking of material flows across warehouse operations.

From a risk management perspective, the organization does not implement a formalized procurement risk management framework. Risk assessment activities are conducted selectively, primarily for critical materials, and are limited to the supplier selection stage. There is no comprehensive, system-wide approach to resilience assessment or continuous risk monitoring across the procurement process. Although supplier relationships are characterized by long-term and collaborative arrangements, they do not include real-time data exchange or integrated risk monitoring mechanisms within the supply network.

The company processes several hundred purchase orders per month and maintains inventory levels of critical materials sufficient to ensure production continuity for several weeks. Despite this buffering capacity, the system remains exposed to disruptions associated with global supply chain dynamics, including lead time variability, component availability constraints, and fluctuations in international transport costs.

Based on the identified characteristics, the system can be considered an appropriate case for illustrating the FHOR-RAM application in environments characterized by heterogeneous digital maturity and incomplete resilience-related information. This makes it a relevant case for illustrating the application of the FHOR-RAM model under realistic industrial conditions characterized by uncertainty, partial data availability, and heterogeneous digital maturity. However, the case study is not intended to demonstrate a fully operational deployment of FHOR-RAM within an organizational IT environment. Instead, it represents an initial application illustrating how existing organizational information, expert knowledge, and qualitative assessments can be structured within the proposed resilience assessment architecture. For the purpose of the FHOR-RAM application, the assessment inputs were derived from multiple organizational information sources reflecting the heterogeneous nature of resilience-related data. These included available ERP and WMS information, supplier performance records, procurement documentation, internal risk-related information, operational observations, and structured expert evaluations provided by representatives involved in procurement and logistics activities. The collected information was not used as a statistical validation dataset, but as a contextual basis for expert-informed linguistic evaluation. Due to the absence of a fully formalized resilience monitoring system within the organization, expert-based linguistic assessments were used to complement available quantitative information. This approach reflects realistic industrial conditions, where resilience assessment frequently requires integration of incomplete operational data and managerial knowledge.

6.2. Mapping of FHOR-RAM Structure to the Case Study

In order to operationalize the FHOR-RAM model in the analyzed procurement system, a structured mapping procedure was performed to align the conceptual framework (Section 5) with the empirical characteristics of the case study. This step ensures consistency between the theoretical House of Resilience (HoR) structure and its practical application, enabling a direct translation of system attributes into model input variables.

In the present case study, a baseline configuration with equal weighting is adopted for both criteria and layers. This implies that all criteria within a given layer are assumed to contribute equally to the layer-level resilience score, while all layers are treated as equally important at the system-level aggregation stage. This assumption is consistent with the exploratory nature of the study and ensures structural neutrality of the evaluation process in the absence of expert-derived preference information. Therefore, no additional preference weights were introduced in the empirical demonstration, and all criteria and layers were treated symmetrically within the fuzzy aggregation structure.

The mapping process involved assigning each evaluation criterion C_{ji} to the corresponding resilience layer L_j, based on its functional role within the procurement and logistics system. The assignment reflects the logical structure of the HoR model, distinguishing between technological and risk-related capabilities (L_1), operational and adaptive capabilities (L_2), structural resilience (L_3), and strategic governance mechanisms (L_4). This mapping procedure is fully consistent with the theoretical structure defined in Section 5, particularly the hierarchical system formulation (Equation (1)), the four-layer HoR architecture (Section 5.2), and the literature-derived criteria set presented in Table 6.

Layer L_1—Technological and risk assessment layer

This layer captures the system's digital maturity, risk awareness, and ability to process and utilize information for decision-making. Based on the case study characteristics, the following mapping was established:

- C_{11}—Real-time monitoring capability:
  Limited real-time visibility due to reliance on ERP-based reporting and delayed data extraction processes (night-time exports), indicating restricted continuous monitoring capability.
- C_{12}—Predictive analytics capability:
  Moderate analytical support provided by BI tools, complemented by spreadsheet-based ad hoc analyses, with limited predictive or real-time forecasting functionality.
- C_{13}—System integration:
  Partial integration between ERP, WMS, and BI systems, ensuring basic interoperability but lacking full real-time synchronization across all decision layers.
- C_{14}—Risk identification and assessment capability:
  Informal and partial risk assessment practices are limited primarily to critical materials and supplier selection stages, without continuous risk monitoring mechanisms.
- C_{15}—Cloud-based infrastructure and data accessibility:
  Conventional on-premise ERP/WMS architecture with restricted real-time accessibility and limited scalability of analytical data processing.

Layer L_2—Operational and adaptive capabilities layer

This layer reflects the system's ability to respond to disruptions through operational flexibility, analytical support, and human adaptability.

- C_{21}—Operational flexibility:
  Moderate flexibility supported by structured procurement and warehouse processes, but constrained by ERP-based procedural rigidity and global supply dependencies.
- C_{22}—Analytical capability:
  Intermediate level of analytical support combining BI tools and spreadsheet-based decision models; however, decision-making remains partially reactive due to delayed data availability.
- C_{23}—Workforce adaptability:
  Relatively high operational adaptability, supported by experienced personnel managing both automated and manual warehouse operations within a hybrid environment.
- C_{24}—Organizational coordination and communication:
  Moderate coordination is enabled by integrated ERP–WMS systems, although cross-functional and cross-organizational information exchange remains limited, particularly in supplier collaboration.

Layer L_3—Structural resilience layer

This layer reflects the robustness and continuity of supply within the procurement system.

- C_{31}—Supplier diversification:
  Limited diversification for finished goods (1–2 suppliers per category), with partial diversification for raw materials sourced globally, indicating moderate dependency risk.
- C_{32}—Lead time stability:
  Significant variability due to global sourcing (especially from China), exposure to transport disruptions, and fluctuating international logistics conditions.
- C_{33}—Critical material availability:
  Moderate buffering through safety stocks ensures several weeks of production continuity; however, vulnerability remains for globally sourced components with unstable supply conditions.

Layer L_4—Strategic resilience layer

This layer captures governance mechanisms, long-term planning, and collaboration strategies.

- C_{41}—Resilience governance maturity:
  Low maturity level, characterized by the absence of formalized procurement resilience frameworks and limited integration of risk management into strategic decision-making.
- C_{42}—Resilience-oriented planning:
  Basic planning practices focused on operational continuity, without structured scenario planning or systematic integration of disruption resilience strategies.
- C_{43}—Collaboration and network strategy:
  Long-term supplier relationships exist; however, collaboration is predominantly transactional and does not include real-time data exchange or joint risk monitoring mechanisms.

The assignment of criteria to specific layers is not arbitrary, but follows a functional decomposition of resilience mechanisms as defined in the HoR framework, ensuring conceptual validity and structural alignment between the model and the empirical system.

The presented mapping translates the empirical characteristics of the procurement system into the formal structure of the FHOR-RAM model, ensuring full alignment between real-world system attributes and theoretical resilience constructs. Each criterion was assigned based on its dominant functional relevance and in accordance with the hierarchical HoR structure, preserving consistency with the aggregation logic defined in Section 5.

This mapping constitutes the foundational step for subsequent fuzzy evaluation (Section 6.3), enabling the transformation of qualitative system characteristics into structured inputs for resilience assessment at both layer and system levels.

6.3. Fuzzy Assessment of the Baseline Scenario

Following the mapping of the FHOR-RAM structure to the analyzed procurement system (Section 6.2), a fuzzy evaluation of the baseline scenario was conducted. The assessment process follows the hierarchical inference mechanism defined in Section 5.4, where linguistic evaluations of individual criteria are transformed into triangular fuzzy numbers (TFNs) and subsequently aggregated at the layer and system levels.

6.3.1. Linguistic Evaluation and Fuzzification of Criteria

Following the mapping procedure presented in Section 6.2, each criterion was evaluated using the five-level linguistic scale defined in Section 5.3. The assigned linguistic values reflect the characteristics of the analyzed procurement system and were derived directly from the qualitative assessment of technological, operational, structural, and strategic capabilities discussed in the previous section.

The linguistic assessments were assigned through a structured qualitative assessment performed by the authors based on the available organizational information and predefined criterion descriptions. The assessment process was not intended to represent an independent statistical validation of the framework, but rather a methodological demonstration of the applicability of the FHOR-RAM model in a real organizational context. Each criterion was evaluated by comparing the available case information with the operational definitions of the resilience criteria provided in Section 5.2.

To improve transparency and reproducibility, each linguistic evaluation was accompanied by a qualitative justification describing the specific organizational evidence supporting the assigned level (Table 13). The Low–Medium–High assessments were therefore derived from predefined criterion descriptions and case-specific observations rather than from subjective assignment without methodological guidance.

Since the current study represents an initial application of the framework, no formal aggregation of multiple independent expert opinions was performed. Consequently, the obtained resilience scores should be interpreted as an illustrative assessment demonstrating the functioning of the FHOR-RAM mechanism rather than as a statistically validated measurement of the absolute resilience level of the organization.

Subsequently, the linguistic assessments were transformed into triangular fuzzy numbers (TFNs) according to the fuzzification procedure described in Section 5.3, using Equations (6)–(8) and the membership functions presented in Tables 8 and 9. This transformation enables the representation of uncertainty and subjectivity inherent in expert-based resilience assessment while preserving the interpretability of the evaluation process.

Table 13 summarizes the linguistic assessments assigned to individual criteria together with the qualitative evidence supporting each evaluation. The inclusion of these justifications is intended to improve transparency and enable replication of the assessment procedure. The corresponding fuzzy representations were automatically generated according to the predefined linguistic scale and subsequently used as inputs to the hierarchical fuzzy aggregation procedure.

Table 13. Fuzzy assessment of resilience criteria (baseline scenario).

Layer	Criterion	Linguistic Value	Justification
L_1	C_{11} Real-time monitoring	Low	Limited real-time visibility and delayed data extraction
L_1	C_{12} Predictive analytics capability	Low	Predominantly descriptive rather than predictive analytics
L_1	C_{13} System integration	Medium	Partial ERP–WMS–BI integration
L_1	C_{14} Risk identification and assessment	Low	Informal risk assessment practices
L_1	C_{15} Cloud infrastructure and accessibility	Low	Limited cloud-based data accessibility
L_2	C_{21} Operational flexibility	Medium	Moderate ability to adjust procurement and warehouse operations
L_2	C_{22} Analytical capability	Medium	BI-supported decision-making with limited advanced analytics
L_2	C_{23} Workforce adaptability	High	Experienced personnel operating in hybrid environments
L_2	C_{24} Organizational coordination	Medium	Internal coordination supported by integrated systems
L_3	C_{31} Supplier diversification	Low	Limited supplier base for key product groups
L_3	C_{32} Lead time stability	Low	Exposure to variability in global sourcing
L_3	C_{33} Critical material availability	Medium	Safety stocks provide temporary buffering capacity
L_4	C_{41} Resilience governance maturity	Low	Absence of formal resilience governance framework
L_4	C_{42} Resilience-oriented planning	Low	Limited use of scenario planning and resilience strategies
L_4	C_{43} Collaboration and network strategy	Medium	Long-term supplier relationships but limited information sharing

6.3.2. Layer-Level Fuzzy Inference and Aggregation

Following the fuzzification stage presented in Section 6.3.1, the obtained linguistic assessments were processed using the first level of the hierarchical fuzzy inference system defined in Section 5.4.1. The fuzzy inference procedure was implemented in MATLAB R2020b using the Fuzzy Logic Toolbox, consistent with the computational framework described in Section 5.4. The implementation included fuzzification of input variables, rule evaluation based on the reduced rule bases presented in Appendix A, aggregation of activated rules, and centroid-based defuzzification according to Equation (13).

At this stage, individual criteria belonging to each resilience layer were aggregated to determine the corresponding layer-level resilience scores R_j. The aggregation process follows the Mamdani inference mechanism described in Section 5.4.2 and consists of four sequential steps:

- fuzzification of criterion evaluations,
- activation of fuzzy rules,
- aggregation of rule outputs,
- defuzzification using the centroid method.

For each layer, the relevant subset of the reduced rule base presented in Appendix A was activated according to the linguistic evaluations obtained in Table 13.

The purpose of this stage is to transform multiple resilience-related criteria into a single resilience score representing the performance of a given HoR layer.

Layer L_1—Technological and risk assessment layer

Layer L_1 is evaluated based on five criteria: $L_1 = \{C_{11}, C_{12}, C_{13}, C_{14}, C_{15}\}$ representing real-time monitoring capability, predictive analytics capability, system integration, risk identification capability, and cloud-based infrastructure accessibility. Based on the assessment presented in Table 13, the linguistic configuration of Layer L_1 can be summarized as:

(Low, Low, Medium, Low, Low)

This configuration activates several rules from the Layer L_1 rule base (Appendix A.2). This configuration reflects the limited digital maturity of the analyzed procurement system. While a moderate level of system integration is achieved through the ERP–WMS–BI environment, the remaining technological and risk-related capabilities remain underdeveloped. In particular, the absence of advanced predictive analytics, restricted real-time monitoring, limited cloud-based accessibility, and only partially formalized risk assessment practices contribute to a generally low resilience profile within this layer.

Consequently, the activated rule set is concentrated primarily within the low-resilience region, with partial activation of neighboring Medium-level rules resulting from the Moderate assessment of system integration (C_{13}). According to the dominance and non-compensatory principles embedded in the FHOR-RAM rule base (Section 5.4.3), the prevalence of low-performing criteria prevents the layer from achieving a moderate resilience outcome despite the presence of one medium-rated capability.

Application of the Mamdani inference mechanism and centroid defuzzification yields: $R_1 = 0.34$. According to the interpretation framework presented in Section 5.5.1, this result corresponds to a Low resilience level.

Layer L_2—Operational and adaptive capabilities

Layer L_2 is composed of $L_2 = \{C_{21}, C_{22}, C_{23}, C_{24}\}$. The linguistic assessment obtained for this layer is:

(Medium, Medium, High, Medium)

The rule activation pattern is dominated by Medium and High resilience rules, particularly due to the relatively strong workforce adaptability represented by criterion C_{23}.

The resulting defuzzified score equals: $R_2 = 0.51$, indicating Moderate resilience.

Layer L_3—Structural resilience layer

Layer L_3 consists of $L_3 = \{C_{31}, C_{32}, C_{33}\}$ corresponding to supplier diversification, lead-time stability, and critical material availability. The assessed linguistic configuration is:

(Low, Low, Medium)

This layer is selected as an illustrative example because its reduced rule base is presented in Appendix B.

The evaluated input combination activates primarily Rules R_{13} and R_{14} together with neighboring fuzzy rules through partial membership activation. Because two of the three criteria are assessed as Low, the inference mechanism shifts the output towards the lower resilience region.

After aggregation and centroid defuzzification, $R_3 = 0.31$, which corresponds to a Low resilience level. This result indicates that the analyzed procurement system remains vulnerable to disruptions caused by supplier dependency and lead-time variability.

Layer L_4—Strategic resilience layer

Layer L_4 includes: $L_4 = \{C_{41}, C_{42}, C_{43}\}$ representing resilience governance maturity, resilience-oriented planning, and collaboration strategy. The obtained linguistic profile is:

$$(\text{Low, Low, Medium})$$

The absence of formal resilience governance mechanisms and structured resilience planning causes activation of predominantly Low-resilience rules.

The resulting resilience score equals: $R_4 = 0.33$, which is also classified as Low resilience.

Summary of layer-level aggregation

Table 14 presents the final resilience scores obtained for each HoR layer.

Table 14. Final Resilience scores for each HoR layer.

Layer	Main Linguistic Pattern	Resilience Score R_j	Interpretation
L_1	L–M–M–L–L	0.34	Low
L_2	M–M–H–M	0.51	Moderate
L_3	L–L–M	0.31	Low
L_4	L–L–M	0.33	Low

All layer-level resilience scores were generated automatically within the MATLAB R2020b environment using the reduced fuzzy rule bases defined in Appendix A and the centroid defuzzification procedure described in Section 5.4.2.

The obtained results are consistent with the observed characteristics of the analyzed procurement system. In particular, the low values of technological, structural, and strategic layers correspond to identified limitations in digital visibility, supplier diversification, and formal resilience governance. The results reveal considerable heterogeneity across the resilience architecture of the analyzed procurement system. The operational and adaptive capabilities represented by Layer L_2 constitute the strongest component of the system, whereas technological, structural, and strategic dimensions remain significantly less developed.

This imbalance suggests that although the organization possesses a certain degree of operational adaptability, its ability to anticipate, absorb, and strategically manage supply chain disruptions remains limited.

6.3.3. System-Level Fuzzy Aggregation

Following the layer-level assessment, the second stage of the FHOR-RAM hierarchical inference process was performed to determine the overall resilience level of the analyzed procurement system. According to the model structure defined in Sections 5.2 and 5.4.1, the resilience scores obtained for Layers L_1–L_4 constitute the inputs to the system-level fuzzy inference system (acc. to Equation (5)). The aggregation was carried out using the system-level Mamdani fuzzy inference mechanism and the reduced rule base presented in Appendix A. Consistent with the baseline assumptions adopted in Section 6.2, equal importance was assigned to all resilience layers. The implementation was performed in MATLAB R2020b using the Fuzzy Logic Toolbox. The MATLAB implementation used in this study should be considered a research prototype supporting model demonstration rather than a final organizational software implementation.

The obtained layer-level resilience profile can be summarized as:

$$(\text{Low, Moderate, Low, Low})$$

indicating that only the operational and adaptive capabilities layer (L_2) achieved a moderate resilience level, while the technological, structural, and strategic layers remained within the low-resilience region. Consequently, the activated system-level rules were predominantly associated with low-to-moderate resilience outcomes.

The system-level inference process and the activation of the corresponding fuzzy rules are illustrated in Figure 4, generated using the Rule Viewer module of MATLAB R2020b Fuzzy Logic Toolbox. The figure provides a graphical representation of the rule activation patterns and the resulting aggregated output, thereby enhancing the transparency and interpretability of the inference process. The visualized inference confirms the contribution of individual resilience layers to the final resilience assessment and illustrates the non-linear aggregation mechanism embedded in the FHOR-RAM framework.

After aggregation and centroid defuzzification, the overall resilience score of the procurement system was obtained as R_{HoR} = 0.402.

The obtained score serves as the baseline resilience assessment and provides the foundation for the diagnostic analysis presented in the following section. However, the obtained value should be interpreted as a model-based diagnostic result derived from structured expert assessment rather than as an empirically measured resilience index. Its primary purpose is to identify relative strengths and weaknesses within the analyzed procurement system and demonstrate the decision-support capability of the FHOR-RAM framework. In addition, the obtained resilience scores should therefore be interpreted as outputs of a theoretically grounded fuzzy assessment model rather than as statistically estimated resilience probabilities.

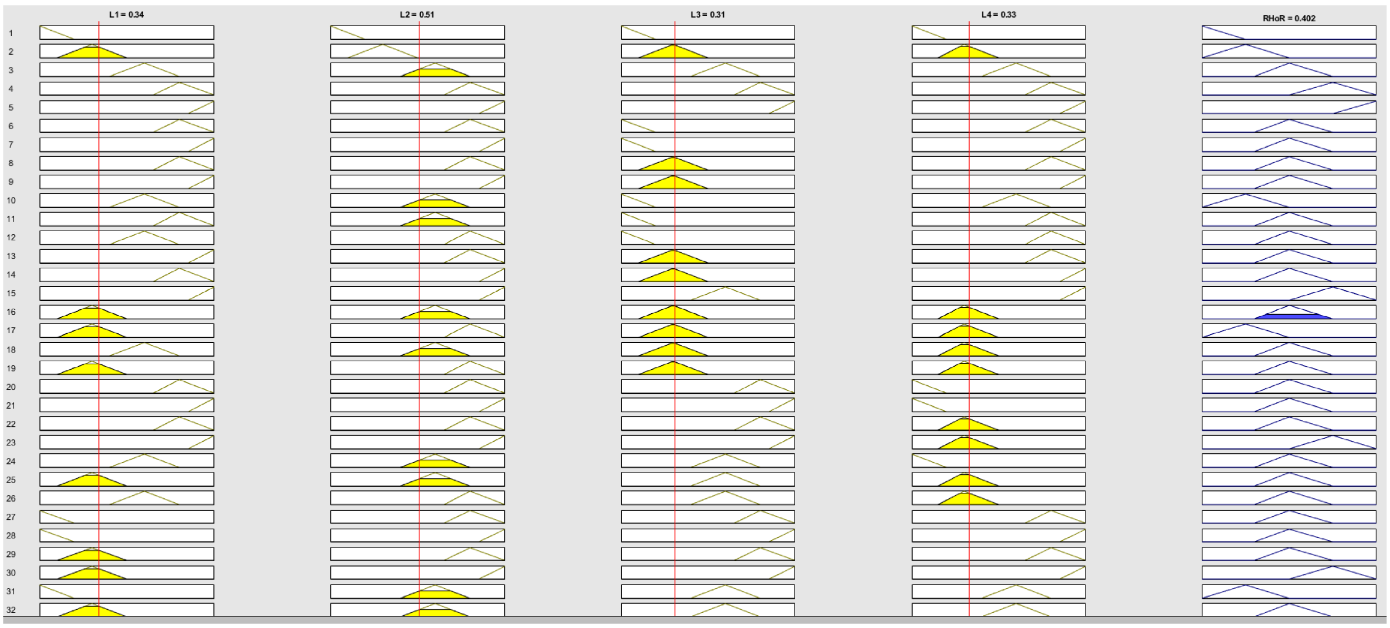

Figure 4. System-level fuzzy inference process and determination of the overall resilience score R_{HoR} using the MATLAB R2020b Rule Viewer.

6.3.4. Interpretation of Resilience Results

According to the resilience interpretation framework presented in Section 5.5.1 (Table 10), this result corresponds to the Moderate resilience level, representing the transition between low and moderate resilience performance. This classification indicates that the procurement system possesses a basic capability to withstand and recover from disruptions; however, its adaptive, anticipatory, and proactive resilience capacities remain insufficiently developed.

The obtained resilience level suggests that the organization is capable of maintaining operational continuity under routine disturbances and moderate supply chain disruptions. This capability is primarily supported by existing inventory buffers, long-term supplier relationships, accumulated operational experience, and relatively strong workforce adaptability. These factors contribute to the system's ability to absorb short-term disruptions and restore normal operations without immediate and severe performance degradation.

At the same time, the resilience score indicates that the procurement system remains vulnerable to more complex, prolonged, or cascading disruption scenarios. Although several resilience-enabling mechanisms are present, they are not yet sufficiently integrated across the entire system architecture. Consequently, resilience is achieved largely through operational adaptation and managerial experience rather than through systematically embedded technological, structural, and strategic resilience mechanisms.

The position of the obtained score at the lower boundary of the Moderate category is particularly noteworthy. It suggests that relatively small deteriorations in critical resilience dimensions could shift the system toward the low-resilience region, whereas targeted improvements in selected resilience drivers could substantially increase the overall resilience level. This observation highlights the importance of examining resilience not only at the aggregate system level but also through the individual resilience layers that contribute to the final assessment.

An additional advantage of the FHOR-RAM model is its multi-level interpretability. Beyond the overall resilience score, resilience can be evaluated at the level of individual criteria and intermediate resilience layers, providing a more detailed understanding of system strengths and weaknesses. Consequently, the overall result should not be interpreted as an isolated performance indicator but rather as a synthesis of interconnected technological, operational, structural, and strategic resilience capabilities. From a managerial perspective, the obtained resilience score serves as an initial diagnostic indicator rather than a direct measure requiring immediate comparison against predefined benchmarks. The main value of the assessment lies in identifying the configuration of resilience capabilities and determining which dimensions require further development. For the analyzed organization, the moderate resilience level indicates that improvement initiatives should not focus exclusively on increasing the overall score, but rather on strengthening the weakest layers that constrain system-level resilience.

Overall, the obtained result indicates that the analyzed procurement system demonstrates an acceptable level of resilience under current operating conditions, but further development of resilience-oriented capabilities is required to achieve a more proactive, adaptive, and strategically embedded resilience profile. The detailed sources of resilience limitations are examined in the subsequent diagnostic analysis.

6.3.5. Diagnostic Analysis of Resilience Weaknesses

One of the principal advantages of the FHOR-RAM framework is its ability to support multi-level diagnostic analysis beyond the final resilience score. While the overall resilience level of the analyzed procurement system was assessed as $R_{HoR} = 0.402$, the hierarchical structure of the model enables decomposition of this result into layer-specific resilience dimensions, facilitating the identification of critical weaknesses and resilience bottlenecks.

The layer-level resilience scores obtained through fuzzy inference are summarized in Table 14. As shown in Table 14, the analyzed procurement system exhibits an uneven resilience profile. The highest resilience level was observed in the Operational and adaptive capabilities layer (L_2), which achieved a score of 0.51 and was classified as Moderate resilience. In contrast, the Technological and Risk Assessment layer (L_1), Structural layer

(L_3), and Strategic layer (L_4) all remained within the Low resilience category, with scores ranging from 0.31 to 0.34.

The obtained results indicate that the procurement system possesses relatively strong operational capabilities but lacks corresponding support from technological, structural, and governance-related resilience mechanisms. Consequently, resilience is not uniformly embedded throughout the system but concentrated primarily within operational practices and workforce adaptability.

Structural Vulnerabilities (L_3)

The lowest resilience score was observed for the Structural layer (R_3 = 0.31). This result reflects weaknesses associated with supplier diversification, lead time stability, and critical material availability. Although the organization maintains safety stock levels sufficient to support production continuity for several weeks, the procurement system remains exposed to risks resulting from global sourcing and limited supplier redundancy. In particular, dependence on a small number of suppliers for selected product groups and exposure to international transportation disruptions contribute significantly to reduced structural robustness.

From a resilience perspective, this finding suggests that the system's capacity to absorb external supply disruptions remains limited, making structural resilience the primary bottleneck within the analyzed procurement system.

Technological and Risk-Management Limitations (L_1)

The Technological and Risk Assessment layer achieved a resilience score of R_1 = 0.34, corresponding to a Low resilience level. This result is largely associated with limited real-time visibility, partial integration of information systems, restricted predictive analytics capability, and the absence of continuous risk monitoring mechanisms. While ERP, WMS, and Business Intelligence solutions are deployed within the organization, analytical processes remain predominantly descriptive rather than predictive.

Furthermore, data extraction limitations and reliance on periodic reporting reduce the organization's ability to detect emerging disruptions proactively. The low score of this layer indicates that the procurement system lacks the digital and analytical capabilities necessary to support resilience-oriented decision-making under rapidly changing supply conditions.

Strategic Resilience Deficiencies (L_4)

The strategic layer obtained a resilience score of R_4 = 0.33, also classified as Low resilience. This result reflects the absence of formal resilience governance mechanisms, limited resilience-oriented planning, and insufficient integration of risk management into long-term procurement strategy. Although supplier relationships are generally stable and long-term in nature, collaboration remains primarily transactional and does not include real-time information sharing or joint risk management initiatives.

The findings suggest that resilience within the organization is managed predominantly at the operational level rather than through structured strategic governance mechanisms. Consequently, the system demonstrates limited preparedness for high-impact disruptions requiring coordinated and long-term response strategies.

Cross-Layer Imbalance Analysis

An important diagnostic insight emerges from the comparison of resilience scores across layers. The operational and adaptive capabilities layer (R_2 = 0.51) substantially outperforms all remaining layers, indicating that operational flexibility, workforce adaptability, and analytical support constitute relative strengths of the organization. However, these strengths are not supported by equivalent levels of technological maturity, structural robustness, or strategic governance.

This imbalance represents a typical resilience asymmetry frequently observed in procurement systems, where organizations rely on employee experience and operational improvisation to compensate for deficiencies in formal resilience mechanisms. While such an approach may be effective during routine disturbances, its effectiveness decreases significantly when facing large-scale or prolonged disruptions.

The FHOR-RAM model explicitly reveals this imbalance by preserving layer-level information throughout the aggregation process, thereby enabling decision-makers to distinguish between operational resilience and systemic resilience.

Based on the diagnostic results, three primary improvement priorities can be identified:

1. Strengthening structural resilience (L_3) through supplier diversification, lead time stabilization initiatives, and enhanced management of critical materials.
2. Enhancing technological resilience (L_1) by implementing real-time monitoring capabilities, predictive analytics tools, improved system integration, and structured risk assessment mechanisms.
3. Developing strategic resilience (L_4) through formal resilience governance frameworks, scenario-based planning, and collaborative risk management with key suppliers.

From a managerial implementation perspective, the identified priorities can be translated into specific resilience improvement actions. For example, the low structural resilience level (L_3) suggests the need for supplier portfolio analysis, identification of critical dependencies, and evaluation of alternative sourcing options. The technological limitations identified within L_1 indicate potential benefits from improving data integration, introducing predictive risk monitoring, and developing more advanced analytical capabilities. Similarly, the strategic weaknesses represented by L_4 suggest the need for formal resilience governance mechanisms, including disruption scenarios, resilience-oriented procurement policies, and structured collaboration with critical suppliers. Therefore, the FHOR-RAM outputs provide not only an assessment of the current resilience configuration but also a structured basis for prioritizing managerial interventions.

The diagnostic analysis, therefore, demonstrates that the overall resilience score of 0.402 is not primarily constrained by operational capabilities, but rather by deficiencies in structural, technological, and strategic resilience dimensions. This finding confirms the value of the FHOR-RAM model as a diagnostic decision-support tool capable of identifying not only the level of resilience but also the underlying sources of resilience weakness within procurement systems.

6.3.6. Scenario-Based What-If Analysis of Resilience Improvement Pathways

To further illustrate the decision-support capabilities of the FHOR-RAM model, a scenario-based what-if analysis was conducted. The objective was not to predict the actual effects of managerial interventions, but to explore how hypothetical changes in resilience layer scores may influence the overall resilience assessment and to demonstrate the model's capability to compare alternative improvement configurations.

The baseline assessment resulted in an overall resilience score of $R_{HoR} = 0.402$, which corresponds to a **moderate resilience level** according to the interpretation framework presented in Section 5.5.1. The obtained result indicates that the analyzed procurement system demonstrates a certain level of resilience capability; however, several areas require improvement, particularly those related to structural stability, strategic preparedness, and technological support.

Following the principles outlined in Section 5.5.3, four hypothetical improvement scenarios were developed. Each scenario represents a realistic managerial intervention targeting a specific resilience layer or a combination of resilience dimensions. The scenarios were designed to evaluate whether improvements concentrated in a single capability area are sufficient to significantly increase overall resilience or whether balanced development across multiple layers is required. The scenarios should be interpreted as exploratory simulations rather than empirically calibrated predictions. The assumed changes in layer scores represent hypothetical improvement states used to investigate the behavior of the fuzzy inference model. They do not directly quantify the expected impact of specific managerial interventions, as establishing such relationships would require longitudinal empirical data, expert elicitation, or validation across multiple organizational contexts.

Scenario A—Technology-oriented improvement

This scenario focuses on strengthening the technological and risk assessment layer (L_1) through:

- implementation of real-time monitoring capabilities,
- enhanced data integration,
- adoption of predictive analytics tools,
- development of cloud-enabled data accessibility.

The linguistic evaluations represented in the model by increasing the linguistic evaluation of criteria C_{11}–C_{15} by one linguistic level, resulting in a simulated layer resilience score change from:

$$\mathrm{R1} = 0.34 \rightarrow 0.70$$

while the remaining resilience layers remained unchanged.

Scenario B—Structural resilience enhancement

This scenario targets the structural resilience layer (L_3), which represents the foundation of the House of Resilience framework. The assumed improvement actions include:

- supplier diversification initiatives,
- development of alternative sourcing strategies,
- increased buffering of critical materials,
- lead-time stabilization measures.

As a result:

$$\mathrm{R3} = 0.31 \rightarrow 0.75$$

while the remaining layers remained at baseline values.

Scenario C—Strategic resilience development

The third scenario addresses weaknesses related to strategic preparedness and governance mechanisms. The assumed interventions include:

- implementation of formal resilience policies,
- resilience-oriented planning procedures,
- supplier collaboration programs,
- integration of resilience considerations into strategic procurement decisions.

Consequently:

$$\mathrm{R4} = 0.33 \rightarrow 0.85$$

while other layers remained unchanged.

Scenario D—Balanced resilience development

The final scenario assumes coordinated improvements across multiple resilience dimensions. In contrast to the previous scenarios, which focused on individual capabilities, this scenario represents a balanced resilience architecture involving simultaneous improvements in technological, structural, and strategic capabilities.

https://doi.org/10.3390/systems14080920

The resulting layer scores were assumed as:

$$R1 = 0.80, R2 = 0.75, R3 = 0.85, R4 = 0.80$$

representing a highly developed and balanced resilience configuration.

Table 15 summarizes the resulting resilience scores obtained for each scenario.

Table 15. Scenario analysis results.

Scenario	Main Intervention	Calculated R_{HoR}	Resilience Level
Baseline	Current state	0.402	Moderate
A	Technological improvement (L_1)	0.519	Moderate
B	Structural improvement (L_3)	0.522	Moderate
C	Strategic improvement (L_4)	0.500	Moderate
D	Balanced multi-layer improvement	0.647	High

The results indicate that improvements focused exclusively on a single resilience dimension lead only to moderate increases in overall resilience. Although each individual intervention improves the targeted resilience capability, the resulting system-level performance remains within the Moderate resilience category.

Among the single-layer interventions, Scenario B (structural resilience enhancement) produces the highest increase in overall resilience, raising the R_{HoR} value from 0.402 to 0.522. This observation is consistent with the HoR assumption that structural resilience may represent an important foundational mechanism within the analyzed configuration. However, because the scenario values were assumed rather than empirically derived, this result should be interpreted as an indication of model behavior rather than evidence of causal dominance. Strengthening supplier networks, reducing dependency on critical sources, and improving supply continuity mechanisms, therefore, represent highly influential resilience improvement pathways.

Scenario C demonstrates that strategic capabilities also significantly contribute to overall resilience. Although governance and planning mechanisms do not directly eliminate operational disruptions, they enable more effective preparation, coordination, and long-term adaptation.

Scenario A illustrates that under the assumed configuration of the model, improvements limited to technological capabilities do not fully compensate for weaknesses in other resilience layers. Despite a substantial increase in technological resilience, the overall resilience improvement remains constrained by weaknesses in other layers. This confirms the non-compensatory logic embedded within the FHOR-RAM model, where advanced technological capabilities cannot fully offset structural or strategic deficiencies.

In contrast, Scenario D demonstrates the strongest improvement potential. By simultaneously increasing several resilience dimensions, the system achieves $R_{HoR} = 0.647$, corresponding to a high resilience level. This finding confirms the systemic nature of resilience represented by the House of Resilience framework, where overall resilience emerges from interactions among structural, operational, technological, and strategic capabilities rather than from excellence in a single dimension.

The scenario analysis demonstrates that FHOR-RAM can support exploratory what-if evaluation and comparison of alternative resilience improvement configurations. However, the prioritization of actual resilience investments would require additional empirical information regarding implementation costs, expected improvement magnitudes, and organizational constraints.

6.3.7. Managerial Implications and Demonstration of FHOR-RAM Applicability

The conducted case study demonstrates the practical applicability of the proposed FHOR-RAM framework for resilience assessment in procurement systems operating under uncertainty and limited data availability. The model was implemented using real organizational data and expert evaluations, enabling a structured assessment of resilience across technological, operational, structural, and strategic dimensions.

The obtained results demonstrate that resilience cannot be adequately represented by a single organizational capability. Instead, the analysis revealed substantial differences between individual resilience layers, highlighting the multidimensional nature of procurement system resilience. While the operational and adaptive capabilities layer (L_2) achieved a moderate resilience level, the technological (L_1), structural (L_3), and strategic (L_4) layers exhibited comparatively weaker performance, resulting in an overall resilience score of $R_{HoR} = 0.402$.

Beyond the final resilience score, the hierarchical structure of the model provided valuable diagnostic insights. The decomposition of resilience into layer-level outputs enabled the identification of critical weaknesses associated with supplier dependency, lead-time instability, limited digital visibility, and insufficient resilience governance mechanisms. Consequently, the assessment moved beyond simple measurement and supported the identification of concrete improvement priorities.

The scenario analysis further demonstrated the usefulness of the model as a decision-support instrument. By evaluating alternative improvement pathways, the analysis showed that isolated interventions generate only limited resilience gains, whereas coordinated improvements across multiple layers lead to substantially higher model-based resilience scores. This finding supports the central assumption of the House of Resilience framework that resilience emerges from the interaction of complementary capabilities rather than from excellence in a single domain.

From a managerial perspective, the proposed framework offers several practical benefits. First, it enables resilience assessment even in environments characterized by incomplete or partially qualitative information. Second, it provides a transparent mechanism for translating expert knowledge into measurable resilience indicators. Third, it supports prioritization of resilience investments by identifying the most influential resilience dimensions and improvement pathways. Finally, its rule-based structure makes it suitable for integration with procurement decision-support systems and future digital-twin-based resilience monitoring environments.

Overall, the case study demonstrates the feasibility and operational relevance of the FHOR-RAM framework. The obtained results illustrate how FHOR-RAM can bridge the gap between conceptual resilience frameworks and practical decision-support needs in procurement and supply chain management. However, the presented case study has several limitations. First, the assessment represents an initial application of the FHOR-RAM framework and does not constitute empirical validation across multiple organizations. Second, the linguistic evaluations were derived from structured expert assessment rather than aggregated expert panels. Third, scenario analysis represents exploratory what-if evaluation rather than prediction of actual intervention outcomes. Future studies should focus on multi-case validation, expert-based calibration of rule bases, and integration with dynamic operational data sources.

7. Discussion

The objective of this study was not only to develop a resilience assessment model but primarily to address the conceptual fragmentation observed in existing resilience frameworks, where technological, operational, structural, and strategic capabilities are frequently analyzed separately without an explicit representation of their interactions. The proposed House of Resilience (HoR) framework addresses an identified conceptual limitation of some existing resilience models, which frequently describe resilience as a collection of independent capabilities or aggregated indicators without explicitly explaining how different resilience mechanisms interact and contribute to the emergence of system-level resilience. The FHOR-RAM model represents the operational extension of this theoretical architecture by introducing a hierarchical fuzzy inference mechanism that enables the representation of nonlinear relationships, interdependencies, and uncertainty inherent in resilience assessment. The proposed FHOR-RAM model addresses the three research questions formulated in Section 1.

RQ1: How can resilience in interconnected logistics systems be conceptualized as an integrated, multi-layer system architecture adaptable across different organizational levels?

The results demonstrate that resilience can be represented as a hierarchical system architecture composed of interdependent resilience dimensions rather than as a single aggregated capability. The proposed House of Resilience (HoR) framework conceptualizes resilience through four complementary layers: technological and risk assessment layer (L_1), operational and adaptive resilience (L_2), structural resilience (L_3), and strategic resilience (L_4). This layered architecture reflects the systemic nature of resilience by recognizing that different resilience capabilities perform distinct functions within the overall organizational system or logistics subsystem being analyzed. Structural resilience contributes to continuity of supply, operational resilience supports adaptive response to disruptions, technological resilience supports visibility and risk awareness, while strategic resilience ensures long-term preparedness and governance. The proposed architecture, therefore, complements existing resilience frameworks by providing an explicit representation of interactions between resilience dimensions within a unified assessment structure. Importantly, the HoR architecture is designed as a general conceptual framework that can be adapted to different organizational levels, including procurement functions, logistics operations, and broader supply chain contexts. However, the empirical application presented in this study focuses specifically on a procurement subsystem of a focal organization and should therefore be interpreted as a demonstration of framework applicability rather than a complete validation of supply chain-wide resilience. Furthermore, because the assessment inputs were derived from structured expert judgment based on case-specific evidence, the obtained resilience scores should be interpreted as diagnostic outputs supporting resilience analysis rather than as empirically measured resilience levels. Therefore, the novelty of the HoR architecture lies not in replacing existing resilience dimensions, but in providing an integrative explanation of their functional interdependencies.

Unlike many existing resilience frameworks, which represent resilience either as a collection of capabilities or as an aggregated performance indicator, the proposed House of Resilience introduces a functional architecture in which resilience emerges from the interaction of complementary organizational layers. Therefore, resilience is not assumed to be the arithmetic sum of individual capabilities, but rather the outcome of their configuration, interaction, and mutual reinforcement within the system architecture. Consequently, the conceptual contribution of this study lies in organizing existing resilience dimensions according to their functional roles and relationships within a coherent system architecture. This architecture provides the conceptual foundation upon which the FHOR-RAM assessment model is subsequently built.

Consequently, the study provides a conceptual answer to RQ1 by demonstrating how resilience can be structured as an integrated multi-layer architecture consistent with systems thinking and resilience engineering principles.

The proposed conceptualization also clarifies the relationship between resilience, organizational performance, and sustainability. In this study, resilience is not considered as an ultimate organizational objective independent from business outcomes, but rather as a strategic capability that enables organizations to maintain operational continuity, improve adaptability, and achieve long-term sustainable performance. Enhanced resilience contributes to business performance by reducing disruption-related losses, improving recovery capabilities, supporting more reliable operations, and enabling faster adaptation to changing environmental conditions. At the same time, resilience capabilities create synergies with sustainability objectives by supporting resource efficiency, responsible decision-making, supply continuity, and long-term value creation. Therefore, resilience and sustainability are not treated as competing objectives, but as interconnected system properties that jointly contribute to organizational robustness and sustainable development. Within the HoR framework, this relationship is reflected particularly through the interaction between structural, technological, operational, and strategic resilience layers, where improvements in individual capabilities contribute to broader organizational and sustainability-oriented outcomes. At the procurement level demonstrated in this study, these benefits are reflected through improved supplier-related risk management and supply continuity, better visibility of critical dependencies, reduced disruption exposure, and more informed sourcing decisions. At broader supply chain levels, these effects depend on interactions with other actors and operational processes.

RQ2: How can such an architecture be operationalized to represent interactions among resilience dimensions and enable structured assessment and decision support under uncertainty?

The proposed FHOR-RAM model operationalizes the House of Resilience architecture through a hierarchical Mamdani fuzzy inference system. The use of fuzzy logic enables the incorporation of expert knowledge and linguistic assessments while addressing uncertainty, ambiguity, and incomplete information commonly encountered in complex logistics and supply chain-related decision contexts. Importantly, fuzzy inference does not constitute the theoretical contribution itself but serves as the operational mechanism that translates the conceptual House of Resilience architecture into an interpretable assessment framework. However, its role extends beyond uncertainty representation. Within FHOR-RAM, fuzzy inference provides a formal mechanism for representing interactions among resilience dimensions and examining their contribution to system-level resilience. Importantly, the nonlinear influence of individual resilience dimensions results from conditional rule-based reasoning rather than from predefined numerical weights, allowing the model to represent bottleneck effects and context-dependent resilience interactions.

The model translates qualitative resilience concepts into measurable assessment criteria and integrates them through a structured rule-based inference mechanism. The hierarchical architecture allows resilience evaluation at multiple levels, from individual criteria through layer-level resilience scores to the overall resilience assessment (R_{HoR}). This structure facilitates transparency, interpretability, and traceability of assessment results, enabling procurement and logistics decision-makers to identify critical weaknesses and prioritize improvement actions. In practical implementation, the FHOR-RAM assessment can be supported by heterogeneous organizational data sources, including ERP and WMS records, supplier performance databases, operational reports, risk management documentation, digital maturity assessments, and structured expert evaluations. The model does not require a single standardized data infrastructure; instead, it integrates quantitative information where available with qualitative managerial knowledge, which is particularly relevant for resilience assessment under uncertainty and incomplete information. The assessment procedure consists of three practical steps: (i) identification and evaluation of resilience criteria based on available organizational evidence, (ii) transformation of linguistic or numerical inputs into fuzzy variables and aggregation through the hierarchical inference mechanism, and (iii) interpretation of system- and layer-level outputs to identify resilience gaps and define improvement priorities. Therefore, FHOR-RAM outputs should be interpreted as diagnostic decision-support information rather than as absolute measurements of resilience performance. The scenario analysis presented in this study should be interpreted as an exploratory what-if application illustrating the behavior of the FHOR-RAM model rather than as a predictive sensitivity analysis. Future research should incorporate empirically derived improvement functions, expert-based calibration, or longitudinal observations to establish stronger links between managerial interventions and resilience development trajectories.

It should also be emphasized that the fuzzy rule base represents a theory-informed interpretation of resilience mechanisms rather than an empirically calibrated causal model. The adopted IF–THEN rules formalize assumptions derived from the conceptual House of Resilience architecture, resilience engineering literature, and procurement domain knowledge. Consequently, the assessment results should be interpreted as being conditional on these modeling assumptions. Alternative expert knowledge, sector-specific requirements, or future empirical evidence may justify modifications of the rule base while preserving the overall conceptual architecture of the FHOR-RAM framework.

The results, therefore, demonstrate that fuzzy hierarchical modeling provides a practical mechanism for transforming a conceptual resilience architecture into an operational decision-support framework. Accordingly, the proposed fuzzy rule base should be interpreted as an explicit and transparent modeling hypothesis that formalizes theory-informed assumptions regarding resilience interactions rather than a universally valid or empirically calibrated representation of resilience behavior. It formalizes theory-informed assumptions regarding resilience interactions and provides an interpretable mechanism for operationalizing the HoR architecture. However, the practical deployment of FHOR-RAM in organizational environments requires additional considerations beyond the computational implementation demonstrated in this study. In particular, maintaining a large fuzzy rule base, updating membership functions, and ensuring consistency of expert-defined assessments may require dedicated organizational capabilities and domain expertise. Therefore, the current study demonstrates methodological feasibility rather than a fully operational enterprise implementation. Nevertheless, the proposed framework provides the essential methodological structure required for future implementation, as the criteria hierarchy, assessment logic, data requirements, and interpretation mechanisms are explicitly defined. Future research should investigate automated rule adaptation, user-friendly interfaces, and integration mechanisms with existing enterprise information systems.

RQ3: What is the role of digital technologies in enhancing resilience across different system layers?

The findings indicate that digitalization should not be interpreted as an independent resilience dimension or as resilience itself. Within the proposed HoR architecture, digital technologies function as enabling capabilities that strengthen resilience by improving sensing, information processing, visibility, coordination, and decision support across multiple resilience layers. Accordingly, digitalization represents a cross-layer enabler rather than a separate category of resilience. Within the proposed framework, digital capabilities are explicitly represented in Layer L_1 as the primary mechanisms supporting sensing, visibility, data integration, predictive analytics, and risk awareness. However, their influence extends beyond L_1 by enabling operational adaptation, supporting structural coordination, and informing strategic decision-making across the remaining resilience layers. In this sense, digital resilience is not treated as an independent type of resilience, but as an enabling capability embedded within the technological and risk assessment layer.

However, the model also demonstrates that technological capabilities alone are insufficient to achieve high resilience. The fuzzy rule base intentionally incorporates limited compensatory effects and bottleneck-oriented reasoning, showing that advanced technological infrastructure cannot fully compensate for weaknesses in operational, structural, or strategic dimensions. This observation is consistent with recent resilience literature emphasizing that resilience emerges from the interaction of technological, organizational, and governance capabilities rather than from digitalization alone [103–105].

The proposed conceptualization also recognizes that digitalization may introduce new sources of vulnerability. Increased reliance on interconnected digital infrastructures may expose logistics systems to cybersecurity threats, data quality deficiencies, algorithmic bias, automation failures, and technological dependence. Consequently, digital transformation should not be viewed as an inherently resilience-enhancing process. Instead, its contribution to resilience depends on appropriate governance, reliable data management, cybersecurity, human oversight, and effective integration with organizational and operational capabilities. This dual role further supports the positioning of digitalization as an enabling capability whose positive effects depend on the maturity of the broader resilience architecture.

The results, therefore, suggest that digital technologies should be viewed as resilience enablers that strengthen visibility, anticipation, and decision support capabilities across the broader resilience architecture while requiring alignment with operational, structural, and strategic capabilities. Moreover, digital capabilities indirectly support sustainability objectives by enabling better resource utilization, reducing inefficiencies, improving transparency, and supporting data-driven decisions that balance resilience and environmental performance [45,47].

An important methodological consideration concerns the derivation and interpretation of the case-study assessment results. In the present study, the linguistic evaluations assigned to individual resilience criteria were obtained through structured expert judgment based on qualitative evidence describing the analyzed procurement system. Therefore, the fuzzy inference results should not be interpreted as direct measurements of absolute resilience performance, but rather as model-based diagnostic outputs generated from a transparent assessment procedure. The purpose of the case application was to demonstrate the applicability of the FHOR-RAM framework, illustrate the representation of resilience interactions, and identify relative strengths and weaknesses within the analyzed system. Future empirical studies should further strengthen the validation of the model through multi-expert assessments, Delphi-based evaluation procedures, longitudinal observations, and data-supported resilience indicators.

Overall, the findings indicate that the HoR framework provides a potentially transferable conceptual architecture, while further empirical studies are required to assess its applicability across different industries, logistics functions, and supply chain configurations. Therefore, the results should be interpreted as preliminary evidence supporting the feasibility of the proposed approach rather than as empirical confirmation of the general validity or transferability of the framework across different industries and supply chain configurations. At the same time, the demonstrated application confirms that the framework can be operationalized within an organizational decision process by linking resilience criteria with available information sources, expert assessments, and managerial improvement actions. Importantly, the study also suggests that resilience in the digital era should not be understood simply as the adoption of advanced digital technologies. Rather, resilience emerges from the balanced integration of digital, organizational, structural, and strategic capabilities, while simultaneously managing the new risks introduced by digital transformation itself. Future research should further examine the applicability of HoR across other logistics functions and multi-actor supply chain configurations.

7.1. Comparison with Existing Resilience Assessment Approaches

Before comparing the proposed FHOR-RAM model with existing resilience assessment approaches, it is important to clarify the conceptual positioning of the underlying House of Resilience (HoR) architecture (Table 16). The contribution of HoR does not consist in introducing new resilience capabilities, as the mechanisms represented by its layers have been extensively discussed within previous research streams. Instead, HoR provides an integrative architectural perspective that structures how heterogeneous resilience mechanisms perform complementary functions and may jointly contribute to system-level resilience.

In contrast to capability-based resilience frameworks, which typically identify and evaluate individual resilience attributes, HoR focuses on the functional relationships among these attributes. Similarly, resilience engineering approaches emphasize the ability to anticipate, monitor, respond, and learn, while dynamic capability perspectives focus on adaptation and transformation; however, these approaches do not explicitly organize technological, operational, structural, and strategic mechanisms into a unified hierarchical architecture. The HoR framework addresses this gap by representing resilience as an interaction between functionally distinct layers rather than as an additive aggregation of independent capabilities.

Table 16. Conceptual positioning of HoR against established resilience perspectives.

Approach	Main Contribution	Aspects Complemented by HoR
Supply chain resilience frameworks [21,22,106]	Identification of resilience capabilities such as redundancy, flexibility, diversification, and collaboration	Limited explicit representation of how different capabilities interact and contribute to system-level resilience
Resilience engineering [107,108]	Anticipation, monitoring, response, and learning capabilities	Primarily focused on resilient performance principles rather than a hierarchical organizational architecture
Systems theory/socio-technical systems [19,62]	Explanation of complex interactions among technological, organizational, and human components	Does not provide a resilience-specific functional architecture
Dynamic capabilities [52,109]	Adaptation, transformation, and strategic renewal under changing environments	Do not explicitly integrate technological sensing, operational adaptation, and structural robustness within a unified resilience architecture
House of Quality/House of Risk [83,86,87]	Structured mapping of relationships among system factors	Designed for prioritization and risk identification rather than modeling resilience emergence
Resilience maturity models [91,110]	Benchmarking capability development levels	Often rely on predefined dimensions and additive assessment logic
HoR (this study)	Multi-layer conceptual architecture integrating technological, operational, structural, and strategic resilience mechanisms	Provides an architectural representation of how different resilience functions can be organized and jointly considered in system-level assessment

Following the conceptual positioning of HoR, the FHOR-RAM model can be compared with existing resilience assessment approaches, multi-agent and autonomous system models, multi-criteria decision-making frameworks, and data-driven machine learning approaches. In contrast to existing studies, FHOR-RAM introduces a unified hierarchical fuzzy architecture that explicitly captures nonlinear interactions between different resilience layers and their underlying capabilities. More importantly, the distinction between HoR and existing approaches is conceptual rather than purely methodological. Existing resilience approaches generally focus on identifying, measuring, or prioritizing resilience capabilities, whereas HoR first defines the architectural relationships through which these capabilities interact and subsequently enables their assessment through FHOR-RAM. Therefore, the primary contribution of the study lies in the HoR architecture, while FHOR-RAM provides the formal mechanism for its operationalization. To provide a structured and compact comparison with existing resilience assessment approaches, the key methodological differences are summarized in Table 17.

Table 17. Comparative analysis of FHOR-RAM versus selected resilience assessment approaches.

Study/Approach	Resilience Representation	Nonlinear Interactions	Uncertainty Handling	Explainability	Decision-Support Capability	Key Limitation vs. FHOR-RAM
Mostafavi (2017) [111]—system-of-systems	Multi-level infrastructure architecture	Partial	Limited	High	Strategic planning support	Lacks explicit operational resilience potentials and functional maturity modeling
Nitsche et al. (2023) [112]—multi-agent systems	Networked autonomous decision systems	Moderate	Limited	Moderate	Scenario-based support	No structured maturity assessment (operational integration and adaptive autonomy not formalized)
Čižiūnienė et al. (2026) [113]—MCDM	Criterion-based resilience evaluation	Limited	High	High	Prioritization of competencies	Linear/additive aggregation; no modeling of interaction effects
Simsek et al. (2025) [114]—ML + MCDM	Data-driven resilience scoring	High	High	Low–Moderate	Predictive decision support	Black-box structure; limited interpretability and rule transparency
Wang (2024) [115]—KPCA indicator model	Indicator-based performance index	High (statistical)	Moderate	Low–Moderate	Performance evaluation	Focus on performance, not resilience mechanisms or causality
FHOR-RAM (this study)	Hierarchical 4-layer resilience architecture	High (rule-based fuzzy inference)	High (linguistic + fuzzy uncertainty)	High (rule-based transparency)	Assessment, diagnosis, and improvement planning	Requires expert knowledge for rule base design (initial calibration effort)

System-of-systems approaches, such as those proposed by Mostafavi [111], emphasize multi-layer infrastructure interdependencies in resilience assessment. However, these models primarily focus on structural representation of infrastructure networks and do not explicitly operationalize resilience as a function of interacting maturity dimensions. In contrast, FHOR-RAM translates system interdependencies into measurable resilience potentials using fuzzy inference, enabling quantitative evaluation of functional resilience evolution rather than static structural representation.

Multi-agent and autonomous system-based approaches, such as those discussed by Nitsche et al. [112], provide valuable insights into decentralized decision-making and emergent behavior in logistics networks. Nevertheless, these models typically lack an explicit maturity-based representation of resilience development and do not integrate structured assessment of organizational and technological integration levels. FHOR-RAM complements this gap by embedding autonomy within the maintaining a hierarchical mapping to functional resilience potentials.

Multi-criteria decision-making approaches, including the one presented in work [113], offer strong interpretability and robustness in uncertain environments. However, many conventional MCDM approaches rely on additive aggregation structures, which may limit their ability to represent nonlinear interactions and bottleneck effects. FHOR-RAM overcomes this limitation by employing a Mamdani-type fuzzy inference system, which allows nonlinear rule-based interactions and enables the representation of both reinforcing effects and bottleneck conditions depending on the defined inference rules.

Machine learning-based and hybrid approaches, such as those given in [114], provide high predictive performance and scalability but often suffer from limited transparency and explainability. In contrast, FHOR-RAM maintains full interpretability through explicit linguistic variables, expert-defined rule bases, and transparent fuzzification and defuzzification processes, making it suitable for decision-support contexts where explainability is essential.

Finally, indicator-based approaches such as [115] rely on dimensionality reduction or statistical aggregation techniques that primarily capture performance efficiency rather than resilience as an emergent system property. FHOR-RAM extends beyond performance measurement by operationalizing resilience as a hierarchical construct consisting of structural enablers, functional resilience capabilities, and system-level assessment outcomes.

More importantly, FHOR-RAM differs from existing approaches not only methodologically but also conceptually. Whereas previous studies primarily focus on evaluating resilience using predefined indicators or capabilities, the proposed framework first defines resilience as a hierarchical functional architecture and subsequently operationalizes this architecture through fuzzy inference. This distinction represents the principal conceptual contribution of the present study, namely the development of an integrative architecture for organizing resilience mechanisms and their interactions. In this context, fuzzy inference should be understood not as a replacement for resilience theory, but as a formal modeling mechanism that enables the theoretical assumptions of HoR, particularly interaction, emergence, and non-compensatory effects, to be represented computationally.

7.2. Contributions, Limitations, and Future Research Directions

The primary contribution of this study is conceptual rather than methodological. Specifically, it introduces the House of Resilience as a hierarchical conceptual architecture that represents resilience as an emergent multi-layer system property resulting from interactions among interconnected capabilities. In contrast to existing approaches that typically assess resilience through isolated capabilities or aggregated indicators, the proposed architecture explicitly defines the functional relationships between technological, operational, structural, and strategic resilience dimensions.

The FHOR-RAM model constitutes an operationalization of this conceptual architecture by translating the proposed resilience structure into a hierarchical fuzzy inference framework for structured resilience assessment under uncertainty. Beyond handling uncertainty, the fuzzy inference mechanism contributes methodologically by enabling the representation of nonlinear relationships and emergent resilience behavior that cannot be adequately captured through additive indicator-based approaches. Consequently, fuzzy inference should be interpreted as the enabling assessment mechanism rather than the primary scientific contribution of the study.

In contrast to many existing resilience assessment approaches, the framework explicitly integrates technological, operational, structural, and strategic dimensions within a single architecture. Furthermore, it provides a transparent mechanism for translating qualitative expert knowledge into a structured resilience evaluation process, thereby bridging conceptual resilience theory and practical assessment procedures.

From a managerial perspective, the FHOR-RAM model provides a structured decision-support methodology for diagnosing potential resilience weaknesses and exploring improvement pathways across technological, operational, structural, and strategic domains. In practical terms, the model supports decision-making by combining organizational data sources (e.g., operational records, supplier information, digital system assessments, and expert evaluations) with a transparent fuzzy inference mechanism. The resulting outputs enable managers to identify resilience bottlenecks, compare alternative improvement scenarios, and prioritize interventions such as supplier diversification, digital capability development, or resilience governance enhancement.

As a result, several limitations should be acknowledged. First, the model relies on theory-informed expert knowledge in the definition of membership functions and fuzzy rules. Consequently, the inference results remain conditional on the adopted modeling assumptions regarding resilience interactions, including the principles of bottleneck effects, limited compensation, and the treatment of critical weaknesses. Although these assumptions are explicitly documented and logically justified, they do not constitute empirically validated causal relationships. Future studies should therefore investigate systematic expert elicitation procedures (e.g., Delphi studies), inter-expert agreement, and data-supported calibration of fuzzy rules to further strengthen the objectivity and reproducibility of the proposed assessment framework. Moreover, while fuzzy inference enables representation of complex interactions, the quality of the obtained resilience assessment depends on the adequacy of the defined rule base. The fuzzy rule base represents theoretically grounded and expert-informed assumptions rather than empirically learned relationships. Consequently, although the current formulation ensures transparency and interpretability, future studies should investigate systematic rule elicitation procedures involving multiple experts, Delphi-based consensus approaches, or data-driven adaptive fuzzy mechanisms. Furthermore, maintaining the model in an organizational setting would require procedures for updating linguistic assessments, membership functions, and fuzzy rules as operational conditions and resilience requirements evolve. Future research should therefore investigate adaptive learning mechanisms that combine expert-driven fuzzy modeling with data-driven calibration. Moreover, future studies should focus on the development of implementation guidelines defining data collection procedures, organizational roles, and integration pathways with existing enterprise systems. In addition, although expert-driven modeling is common in fuzzy systems and resilience assessment, the resulting outputs remain influenced by subjective judgments. In addition, the current implementation adopts an equal-weighting assumption for both criteria and resilience layers. Although this assumption ensures methodological transparency and facilitates model interpretation, future studies could integrate weighting approaches such as the Analytic Hierarchy Process (AHP) to reflect expert preferences and assess the influence of differentiated importance among resilience factors.

Second, despite the rule reduction procedure, the fuzzy rule base remains relatively extensive. While the hierarchical architecture improves interpretability and computational efficiency, further optimization methods could be explored for larger-scale applications.

Third, the proposed framework was demonstrated through an initial procurement-oriented case study. Although the case study demonstrates the feasibility of applying the approach in the investigated context, it does not constitute a full empirical validation of the model. Therefore, caution should be exercised when generalizing the results to other industrial sectors or supply chain contexts.

https://doi.org/10.3390/systems14080920

Fourth, the current model assumes static membership functions and rule structures. In practice, resilience capabilities evolve over time, suggesting opportunities for developing adaptive or self-learning fuzzy inference systems.

Furthermore, the scenario-based analyses performed in this study illustrate possible resilience improvement pathways but do not quantify the actual effects of managerial interventions. Establishing such relationships requires further empirical validation based on longitudinal and multi-case studies. Therefore, these analyses should be interpreted as exploratory what-if simulations demonstrating model behavior rather than as predictions of organizational performance improvements.

Future research should, therefore, focus on broader empirical studies across multiple industries and supply chain configurations, comparative benchmarking against alternative resilience assessment methods, and investigation of implementation aspects related to data integration, model governance, and adaptive updating mechanisms.

8. Conclusions

This study introduced the House of Resilience (HoR) as a hierarchical conceptual architecture that represents resilience as an emergent system property adaptable across different organizational levels. Unlike approaches that assess resilience through isolated capabilities or aggregated indicators, the proposed architecture explicitly defines functional relationships among technological and risk assessment, operational and adaptive, structural, and strategic resilience dimensions. By organizing these interdependent layers within a unified framework, HoR contributes to a more integrated understanding of resilience mechanisms and their role in generating system-level resilience. The contribution of HoR does not lie in identifying new resilience factors, but in providing a functional architecture that explains how established resilience mechanisms interact and jointly shape resilience outcomes.

The proposed FHOR-RAM model operationalizes this conceptual architecture through a hierarchical Mamdani fuzzy inference system. Rather than constituting the primary contribution itself, fuzzy inference serves as the operational mechanism that translates the theoretical House of Resilience architecture into an interpretable assessment and decision-support framework for logistics-related contexts. Importantly, fuzzy inference not only addresses uncertainty associated with expert judgments but also enables the representation of nonlinear relationships, interaction effects, and non-compensatory resilience mechanisms assumed by the HoR architecture. A key methodological contribution of the study is therefore the development of a hierarchical fuzzy rule-based mechanism that operationalizes the House of Resilience concept and enables computational representation of the proposed resilience relationships.

The results indicate that resilience in the digital era should not be interpreted as a direct consequence of technology adoption alone. While digital technologies significantly enhance visibility, risk awareness, information processing, and decision support, they function primarily as enabling capabilities supporting resilience across multiple organizational layers. At the same time, digital transformation may introduce new vulnerabilities related to cybersecurity, data quality, technological dependence, or automation failures. Consequently, high resilience emerges not from digitalization itself but from the balanced integration of digital, operational, structural, and strategic capabilities supported by appropriate governance. This finding supports the conceptual premise of the HoR framework that resilience cannot be adequately represented as an additive accumulation of independent capabilities. The proposed model, therefore, highlights the importance of adopting a holistic resilience perspective that extends beyond individual technologies or isolated organizational functions. Taken together, the findings provide answers to the three research questions formulated in Section 1. First, resilience can be conceptualized as a multi-layer architecture integrating structural, operational, technological, and strategic dimensions that can be adapted to different organizational levels. Second, this architecture can be operationalized through a hierarchical fuzzy inference framework that supports resilience assessment under uncertainty. Third, the findings confirm that digital technologies act as important resilience enablers, although their effectiveness depends on their integration with broader organizational and governance capabilities.

The procurement case study demonstrated one specific application of the FHOR-RAM model within a focal organization's procurement subsystem. The case study should therefore be considered an initial illustration of the framework implementation rather than a comprehensive validation study. Indeed, although the study provides evidence of the model's practical feasibility within the investigated procurement context, the results should be interpreted as a verification of applicability rather than a full empirical validation. Nevertheless, the case study illustrates that the proposed conceptual architecture can be consistently translated into an operational assessment procedure capable of supporting resilience diagnosis and improvement planning in real procurement systems. Accordingly, the empirical findings should not be generalized directly to complete supply chain networks but should be interpreted as evidence supporting the applicability of the proposed architecture at the procurement level. Consequently, further research is required to assess the robustness and transferability of the model across different industries, supply chain structures, and organizational contexts. Since the case assessment was based on structured expert judgment, future research should also further validate the framework through independent multi-expert evaluations and empirical resilience measurements.

It should also be emphasized that the proposed set of fifteen assessment criteria represents a theoretically grounded and context-specific operationalization of the HoR architecture rather than an exhaustive representation of all possible resilience determinants. While the four-layer architecture provides a transferable conceptual structure, the selection and allocation of specific criteria may require adaptation depending on the characteristics of the analyzed logistics subsystem, industry context, and decision-making level.

Further research is required to validate the framework across different industrial contexts, investigate alternative weighting approaches (e.g., AHP or fuzzy AHP) for differentiating the relative importance of resilience criteria and layers, examine the content validity of criteria sets across different logistics subsystems, and explore its integration with advanced decision-support systems, digital twins, and adaptive AI-supported fuzzy inference mechanisms capable of learning and updating resilience relationships over time. Furthermore, future studies should investigate the practical deployment aspects of FHOR-RAM, including scalability, rule base maintenance, user interaction, and integration with existing organizational information systems.

Overall, the contribution of this study lies in providing a conceptual and methodological framework that can support future resilience analysis in different contexts, subject to further empirical validation. By distinguishing between resilience as a systemic organizational capability and digitalization as an enabling cross-layer capability, the study contributes to a more precise conceptual understanding of resilience in digitally transformed logistics systems. At the same time, empirical validation across broader logistics and supply chain configurations remains an important direction for future research.

Author Contributions: Conceptualization, A.A.T. and S.W.-W.; methodology, A.A.T. and S.W.-W.; formal analysis, A.A.T. and S.W.-W.; resources, A.A.T. and S.W.-W.; data curation, A.A.T. and S.W.-W.; writing—original draft preparation, A.A.T. and S.W.-W.; writing—review and editing, A.A.T. and S.W.-W.; visualization, A.A.T. and S.W.-W. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The original contributions presented in this study are included in the article. Further inquiries can be directed to the corresponding author.

Conflicts of Interest: The authors declare no conflicts of interest.

Abbreviations

The following abbreviations are used in this manuscript:

ABM	Agent-based Modelling
AI	Artificial Intelligence
AS/RS	Automated Storage and Retrieval System
BI	Business Intelligence
DES	Discrete-Event Simulation
DSS	Decision Support System
ERP	Enterprise Resource Planning
FHOR-RAM	Fuzzy House of Resilience Assessment Model
FIS	Fuzzy Inference System
HoR	House of Resilience
IoT	Internet of Things
IT	Information Technology
KPCA	Kernel Principal Component Analysis
ML	Machine Learning
RP	Resilience Potential
SDM	System Dynamics Modeling
SME	Small and Medium-sized Enterprises
TPS	Toyota Production System
TFN	Triangular Fuzzy Number
WMS	Warehouse Management System

Appendix A. Detailed Fuzzy Rule Bases for FHOR-RAM Model

Appendix A.1. Rule Base Development Principles

The fuzzy rule bases presented in this appendix were developed according to the principles described in Section 5.4.3. The rule bases presented in this appendix represent theory-informed expert assumptions regarding the relationships between resilience capabilities and system-level resilience outcomes. They were not derived from statistical learning or historical performance datasets; instead, they were constructed based on the functional logic of the House of Resilience framework, established resilience engineering principles, and procurement resilience mechanisms identified in the literature.

The FHOR-RAM model employs a hierarchical Mamdani fuzzy inference system in which the relationships between resilience criteria, layer-level resilience, and overall resilience are represented through expert-defined fuzzy rules. Because the theoretical number of possible rule combinations grows exponentially with the number of input variables, a structured rule reduction procedure was adopted.

The objective of the reduction process was to preserve the essential behavioral characteristics of the resilience system while maintaining interpretability, computational efficiency, and reproducibility.

For a layer containing n_j criteria and a linguistic scale consisting of five linguistic terms (*VL*, *L*, *M*, *H*, *VH*), the theoretical number of possible rules is $N_j = 5^{nj}$. Consequently, the theoretical rule space of the FHOR-RAM model exceeds 4500 possible rules (Table 9), making complete enumeration impractical.

To address this issue, the final rule bases were developed according to five systematic reduction principles.

Appendix A.1.1. Rule Elicitation and Consistency Assessment

The development of the fuzzy rule base followed a structured elicitation procedure consisting of four steps, which are defined in Table A1:

(i) identification of the functional role of each resilience layer within the HoR architecture,
(ii) determination of expected relationships between criteria and layer-level resilience based on literature-derived resilience mechanisms,
(iii) translation of these relationships into linguistic IF–THEN rules using the predefined five-level linguistic scale,
(iv) consistency assessment of the resulting rule sets with respect to monotonicity, boundary conditions, and non-compensatory assumptions.

To improve methodological transparency, Table A1 summarizes the origin of the knowledge incorporated into the fuzzy rule base and clarifies the specific role played by each source during rule development. As shown, the rule base was not derived from empirical datasets or statistical learning. Instead, it represents a theory-informed synthesis performed by the authors, integrating conceptual assumptions, published resilience knowledge, and domain expertise into a coherent set of linguistic IF–THEN rules.

Table A1. Sources underlying the development of the fuzzy rule base.

Source of Knowledge	Contribution to Rule Development	Example of Resulting Modelling Assumption
House of Resilience (HoR) conceptual architecture	Defined the functional role of each resilience layer and the expected interactions between layers	Structural resilience provides the foundational conditions supporting higher-level resilience capabilities
Resilience engineering and supply chain resilience literature	Identified commonly recognized resilience mechanisms and expected relationships between capabilities	Critical weaknesses cannot always be compensated by strengths in other resilience dimensions (non-compensatory behavior)
Procurement and supply chain domain knowledge	Supported the interpretation of resilience mechanisms within procurement decision contexts	Supplier diversification and material availability strongly influence structural resilience under disruption conditions
Authors' theory-informed synthesis	Translated the conceptual assumptions into linguistic IF–THEN fuzzy rules and organized the reduced rule base	Definition of majority-based, dominance-based, boundary-condition, and limited-compensation rules

The consistency assessment aimed to ensure that higher input capability levels did not produce lower resilience outputs and that critical weaknesses were appropriately reflected in the inference mechanism.

Consequently, the proposed fuzzy rule base should be interpreted as an explicit operationalization of the theoretical assumptions underlying the HoR framework rather than as a statistically calibrated or universally validated knowledge base. Its primary purpose is to provide a transparent and reproducible reasoning structure that can be refined through future expert elicitation procedures or empirical calibration.

Table A2. Relationship between fuzzy rule design principles and HoR assumptions.

Rule Design Principle	Modelling Assumption	Relationship with HoR Architecture
Preservation of boundary conditions	Extreme system states should lead to corresponding resilience outcomes	Ensures logical consistency between very weak/very strong capability configurations and emergent resilience levels
Majority-based evaluation	Dominant capability patterns influence the resulting resilience level	Reflects the assumption that resilience emerges from combined performance of multiple interacting capabilities
Dominance of critical weaknesses	Severe deficiencies in critical dimensions may constrain overall resilience	Represents the non-compensatory nature of resilience mechanisms within the HoR layers
Limited compensation	Strong capabilities may partially mitigate moderate weaknesses but cannot eliminate critical vulnerabilities	Captures interaction effects between resilience dimensions
Monotonicity constraint	Improvement in input capabilities should not reduce resilience outcome	Maintains logical consistency of the fuzzy inference mechanism

Appendix A.1.2. Principle 1: Preservation of Boundary Conditions

The first group of rules defines the extreme limits of system behavior and guarantees logical consistency of the model. For each layer, the following boundary rules are included:

Worst-case rule

$$\text{IF} \mid all/inputs = VL \text{ THEN} \mid output = VL$$

Best-case rule

$$\text{IF} \mid all/inputs = VH \text{ THEN} \mid output = VH$$

In addition, homogeneous configurations for the intermediate linguistic levels are included:

$$(L, L, L, \ldots) \to L$$

$$(M, M, M, \ldots) \to M$$

$$(H, H, H, \ldots) \to H$$

These rules establish the fundamental behavior of the inference system and ensure that identical input assessments produce identical output assessments.

Appendix A.1.3. Principle 2: Majority-Based Evaluation

The second group of rules reflects the assumption that resilience is primarily determined by the dominant performance level among the criteria.

For example:

$$\text{IF} \mid majority/of/inputs = H \text{ THEN}/output = H$$

and

$$\text{IF} \mid majority/of/inputs = M \text{ THEN} \mid output = M$$

This principle captures typical real-world situations where resilience emerges from the overall condition of the system rather than from a single criterion. Representative examples are presented in Table A3.

Table A3. The exemplary rules configuration for Principle 2.

Input Configuration	Output
H–H–M	H
H–M–H	H
M–M–H	M
M–H–M	M

Appendix A.1.4. Principle 3: Dominance of Critical Weaknesses

The FHOR-RAM model adopts a partially non-compensatory resilience logic. This assumption reflects the observation that severe weaknesses in critical resilience dimensions may substantially degrade overall resilience, even when other dimensions perform well. Therefore, dedicated rules are introduced to penalize configurations containing very low assessments.

Examples include:

$$\text{IF} \mid C_i = VL \text{ AND} \mid C_k \leq L \text{ AND THEN} \mid output \leq L$$

Typical examples are given in the table below.

Table A4. The exemplary rules configuration for Principle 3.

Configuration	Output
VL–VL–H	VL
VL–L–H	L
VL–M–H	L
VL–H–H	M

This mechanism prevents unrealistic full compensation of critical vulnerabilities.

Appendix A.1.5. Principle 4: Limited Compensation

Although the model follows a predominantly non-compensatory logic, limited compensation is permitted for intermediate conditions.

For example:

$$(M, M, H) \to M$$

rather than

$$(M, M, H) \to H$$

Similarly:

$$(VH, M, M) \to H$$

instead of

$$VH$$

This principle reflects the practical reality that strong performance in one area may improve resilience, but cannot fully offset weaknesses in other important dimensions.

Appendix A.1.6. Principle 5: Elimination of Redundant Permutations

Many input combinations differ only in the ordering of criteria while representing identical logical situations. For example: (H, M, M), (M, H, M), (M, M, H) all represent the same majority-based scenario. Rather than defining separate rules for each permutation, a single representative rule is retained.

This procedure substantially reduces the size of the rule base while preserving the semantic meaning of the inference process.

The resulting rule bases preserve the key nonlinear relationships between resilience dimensions while remaining sufficiently compact for expert validation and practical implementation. Furthermore, owing to the use of overlapping fuzzy membership functions and Mamdani inference, the model is capable of interpolating between explicitly defined rules, ensuring smooth transitions throughout the input space despite the reduced number of rules.

Appendix A.2. Rule Base for Layer L_1—Technological and Risk Assessment Layer

Layer L_1 represents the technological and risk-awareness foundation of the procurement resilience system. It captures the organization's capability to monitor operations, process information, identify emerging threats, and support decision-making through digital technologies.

The layer is defined by five criteria:

- C_{11}—Real-time monitoring,
- C_{12}—Predictive analytics capability,
- C_{13}—System integration,
- C_{14}—Risk identification and assessment capability,
- C_{15}—Cloud-based infrastructure and data accessibility.

The output variable is:

- L_1—Technological and risk assessment.

For a five-input system using five linguistic terms (VL, L, M, H, VH), the theoretical rule space consists of $N_{L1} = 5^5 = 3125$ possible combinations. Following the reduction procedure described in Appendix A.1, the final rule base consists of 45 representative rules that capture the dominant behavioral patterns of the technological resilience layer.

The rule structure was designed according to five groups of rules:

- boundary-condition rules,
- risk-dominance rules,
- cloud and integration rules,
- balanced operational scenarios,
- high-performance scenarios.

The resulting rule base is summarized in Table A5.

Table A5. Structure of the rule base for Layer L_1.

Rule Category	Number of Rules	Purpose
Boundary rules	5	Definition of extreme system states
Risk-dominance rules	13	Capturing the critical role of risk awareness
Cloud & integration rules	10	Reflecting technological interoperability effects
Balanced scenarios	10	Typical operating conditions
High-performance scenarios	10	Advanced digital resilience configurations
Total	48	

Appendix A.2.1. Boundary-Condition Rules for Layer L_1

The first group defines the limits of technological resilience performance (Table A6). These rules establish monotonic behavior and ensure consistency between homogeneous input and output assessments.

Table A6. Boundary-condition rules for L_1.

Rule ID	C_{11}	C_{12}	C_{13}	C_{14}	C_{15}	Output L_1
L1-R1	VL	VL	VL	VL	VL	VL
L1-R2	L	L	L	L	L	L
L1-R3	M	M	M	M	M	M
L1-R4	H	H	H	H	H	H
L1-R5	VH	VH	VH	VH	VH	VH

Appendix A.2.2. Risk-Dominance Rules for Layer L_1

The second group reflects the assumption that technological infrastructure alone is insufficient if the organization lacks the capability to identify and assess risks. Accordingly, low values of C_{14} may significantly reduce overall technological resilience. The set of rules is given in Table A7.

Table A7. Risk-dominance rules for L_1.

Rule ID	C_{11}	C_{12}	C_{13}	C_{14}	C_{15}	Output L_1
L1-R6	H	H	H	VL	H	M
L1-R7	VH	VH	H	VL	VH	M
L1-R8	H	VH	H	L	H	M
L1-R9	VH	H	VH	L	VH	M
L1-R10	M	M	M	VH	M	M
L1-R11	L	M	M	VH	M	M
L1-R12	M	L	M	VH	M	M
L1-R13	H	M	M	VH	M	H
L1-R14	H	H	M	VH	M	H
L1-R15	VH	H	H	VH	H	VH
L1-R16	M	M	L	VH	L	M
L1-R17	L	M	M	VH	M	M
L1-R18	M	L	M	VH	M	M

These rules ensure that resilience awareness remains a central component of technological resilience and prevent unrealistic overestimation caused solely by digital infrastructure.

Appendix A.2.3. Cloud and Integration Rules for Layer L_1

The third group captures the role of digital connectivity, interoperability, and cloud-enabled information accessibility (Table A8). These rules reflect the increasing importance of cloud-enabled data availability and system interoperability for achieving supply chain visibility and resilience.

Table A8. Cloud and integration rules for L_1.

Rule ID	C_{11}	C_{12}	C_{13}	C_{14}	C_{15}	Output L_1
L1-R19	H	H	VL	H	H	M
L1-R20	H	H	L	H	H	M
L1-R21	VH	H	VL	VH	H	M
L1-R22	VH	VH	L	H	H	H
L1-R23	M	M	VH	M	VH	H
L1-R24	H	M	VH	H	VH	H
L1-R25	H	H	VH	H	VH	H
L1-R26	VH	H	VH	VH	VH	VH
L1-R27	M	H	H	M	VH	H
L1-R28	H	VH	H	H	VH	H

Appendix A.2.4. Balanced Operational Scenarios for Layer L_1

The fourth group represents realistic intermediate configurations typically encountered in procurement environments (Table A9). These rules implement the majority-based evaluation principle described in Appendix A.1.

Table A9. Balanced scenarios for L_1.

Rule ID	C_{11}	C_{12}	C_{13}	C_{14}	C_{15}	Output L_1
L1-R29	M	M	M	H	M	M
L1-R30	M	M	H	M	M	M
L1-R31	H	M	M	M	M	M
L1-R32	M	H	M	M	M	M
L1-R33	M	M	M	M	H	M
L1-R34	H	H	M	M	M	H
L1-R35	H	M	H	M	M	H
L1-R36	M	H	H	M	M	H
L1-R37	H	M	M	H	M	H
L1-R38	M	H	M	H	M	H

Appendix A.2.5. High-Performance Scenarios for Layer L_1

The final group represents digitally mature procurement systems exhibiting strong technological resilience (Table A10).

Table A10. High-performance scenarios for L_1.

Rule ID	C_{11}	C_{12}	C_{13}	C_{14}	C_{15}	Output L_1
L1-R39	VH	VH	H	H	H	VH
L1-R40	VH	H	VH	H	H	VH
L1-R41	H	VH	VH	H	H	VH
L1-R42	VH	H	H	VH	H	VH
L1-R43	VH	H	H	H	VH	VH
L1-R44	VH	VH	VH	H	H	VH
L1-R45	VH	VH	H	VH	H	VH
L1-R46	VH	H	VH	VH	H	VH
L1-R47	H	VH	VH	VH	H	VH
L1-R48	VH	VH	VH	VH	H	VH

Overall, the proposed rule base reflects the assumption that technological resilience emerges from the interaction between digital visibility, predictive capability, technological integration, cloud-enabled information accessibility, and systematic risk awareness. The rule structure preserves the non-linear and partially non-compensatory nature of resilience while ensuring interpretability and consistency with the technological foundation layer of the House of Resilience framework.

Appendix A.3. Rule Base for Layer L_2—Operational and Adaptive Capabilities

Layer L_2 represents the adaptive capabilities of the procurement system and reflects its ability to respond, adjust, and recover from disruptions through operational, analytical, human, and organizational resources. In accordance with the House of Resilience framework, this layer corresponds to the central pillars supporting resilience performance and operational continuity.

The layer is defined by four criteria:

- C_{21}: Operational flexibility,
- C_{22}: Analytical capability,
- C_{23}: Workforce adaptability,

- C_{24}: Organizational coordination and communication.

  The output variable is:

- L_2: Operational and adaptive resilience.

The complete theoretical rule space contains $N_{L2} = 5^4 = 625$ possible combinations. Following the reduction methodology described in Section 5.4.3, the final rule base consists of 35 representative rules. The selected rules capture the dominant behavioral patterns of the layer while preserving interpretability and ensuring sufficient coverage of the input space.

The rule structure reflects four key assumptions:

1. Adaptive resilience is multidimensional and depends simultaneously on operational, analytical, human, and organizational capabilities.
2. Workforce adaptability (C_{23}) plays a critical role in disruption response because even advanced analytical tools and flexible processes cannot be effectively utilized without competent personnel.
3. Organizational coordination and communication (C_{24}) act as an integrating mechanism linking operational and analytical activities.
4. The layer follows a partially compensatory logic, meaning that strong performance in one dimension may partially offset medium-level deficiencies, but cannot fully compensate for severe weaknesses.

To ensure transparency, the final rule base is organized into five groups.

Appendix A.3.1. Boundary Rules for Layer L_2

Boundary rules define the extreme limits of system behavior and establish direct correspondence between homogeneous input conditions and resilience outcomes.

Table A11. Boundary rules for Layer L_2.

Rule ID	C_{21}	C_{22}	C_{23}	C_{24}	Output L_2
L2-R1	VL	VL	VL	VL	VL
L2-R2	L	L	L	L	L
L2-R3	M	M	M	M	M
L2-R4	H	H	H	H	H
L2-R5	VH	VH	VH	VH	VH

Appendix A.3.2. Workforce-Dominance Rules for Layer L_2

These rules reflect situations in which workforce adaptability becomes the dominant determinant of resilience performance. Low workforce adaptability limits the effectiveness of otherwise capable systems, whereas highly adaptive personnel enhance resilience under uncertain conditions.

Table A12. Workforce-dominance rules for Layer L_2.

Rule ID	C_{21}	C_{22}	C_{23}	C_{24}	Output L_2
L2-R6	H	H	VL	H	M
L2-R7	VH	H	VL	VH	M
L2-R8	M	M	VL	M	L
L2-R9	H	M	VL	H	M
L2-R10	VH	VH	L	VH	H
L2-R11	H	H	L	H	M
L2-R12	M	H	VH	M	H
L2-R13	H	M	VH	H	H

The above rules operationalize the assumption that workforce adaptability acts as a critical enabler of resilience realization.

Appendix A.3.3. Organizational Coordination and Communication Dominance Rules for Layer L_2

These rules capture situations where resilience performance is constrained by ineffective communication and coordination mechanisms. Even highly flexible and analytically capable organizations may struggle to respond effectively when information exchange is inadequate.

Table A13. Coordination-dominance rules for Layer L_2.

Rule ID	C_{21}	C_{22}	C_{23}	C_{24}	Output L_2
L2-R14	H	H	H	VL	M
L2-R15	VH	VH	H	VL	M
L2-R16	M	M	M	VL	L
L2-R17	H	M	H	VL	M
L2-R18	VH	H	VH	L	H
L2-R19	H	H	H	L	M
L2-R20	M	H	M	VH	M

These rules emphasize the role of organizational coordination as a resilience integrator linking operational, analytical, and human capabilities.

Appendix A.3.4. Balanced Operational Scenarios Layer L_2

Balanced rules represent realistic situations where performance across criteria is relatively consistent. These configurations constitute the reference states of the system.

Table A14. Balanced scenarios for Layer L_2.

Rule ID	C_{21}	C_{22}	C_{23}	C_{24}	Output L_2
L2-R21	M	M	H	M	M
L2-R22	M	H	M	M	M
L2-R23	H	M	M	M	M
L2-R24	M	M	M	H	M
L2-R25	H	H	M	M	H
L2-R26	M	H	H	M	H
L2-R27	H	M	H	M	H

These rules describe gradual transitions between medium and high resilience states.

Appendix A.3.5. High-Performance Resilience Scenarios for Layer L_2

The final group represents highly resilient operational configurations characterized by strong performance across most or all criteria.

Table A15. High-performance scenarios for Layer L_2.

Rule ID	C_{21}	C_{22}	C_{23}	C_{24}	Output L_2
L2-R28	H	H	H	M	H
L2-R29	H	H	M	H	H
L2-R30	H	M	H	H	H
L2-R31	M	H	H	H	H
L2-R32	VH	H	H	H	VH
L2-R33	H	VH	H	H	VH
L2-R34	H	H	VH	H	VH
L2-R35	H	H	H	VH	VH

These rules reflect the assumption that resilience reaches the highest level when operational, analytical, human, and organizational capabilities simultaneously demonstrate superior performance.

The final Layer L_2 rule base consists of 35 rules (Table A16).

Table A16. Final set of rules for Layer L_2.

Rule Category	Number of Rules
Boundary rules	5
Workforce-dominance rules	8
Coordination-dominance rules	7
Balanced scenarios	7
High-performance scenarios	8
Total	35

The proposed rule base captures the dominant mechanisms governing operational resilience while maintaining a manageable level of complexity. Together with the fuzzy interpolation capabilities of the Mamdani inference system, these rules provide continuous and interpretable resilience assessments across the entire input space.

Appendix A.4. Rule Base for Layer L4—Strategic Resilience

Layer L_4 represents the strategic dimension of resilience and reflects the organization's ability to institutionalize resilience principles, develop long-term preparedness mechanisms, and maintain collaborative relationships across the supply network. Unlike the lower layers, which focus primarily on operational and structural capabilities, L4 captures the governance mechanisms that enable resilience to be sustained and continuously improved over time.

The layer is defined by three criteria:

- C_{41}: Resilience governance maturity,
- C_{42}: Resilience-oriented planning,
- C_{43}: Collaboration and network strategy.

The output variable is:

- L_4: Strategic resilience.

The complete theoretical rule space contains $N_{L4} = 5^3 = 125$ possible rule combinations. Following the reduction methodology presented in Section 5.4.3, the final rule base consists of 30 representative rules capturing the dominant strategic resilience patterns while maintaining transparency and interpretability.

The rule design is based on four strategic assumptions:

1. Resilience governance maturity (C_{41}) provides the institutional foundation for resilience management and therefore strongly influences strategic resilience outcomes.
2. Resilience-oriented planning (C_{42}) determines preparedness for future disruptions through contingency planning, scenario analysis, and long-term resilience investments.
3. Collaboration and network strategy (C_{43}) reflects the organization's ability to leverage external relationships and jointly build resilience across the supply chain.
4. Strategic resilience exhibits a partially non-compensatory character, meaning that severe deficiencies in governance, planning, or collaboration cannot be fully offset by excellence in other dimensions.

To improve interpretability, the final rule base is organized into five groups.

https://doi.org/10.3390/systems14080920

Appendix A.4.1. Boundary Rules for Layer L_4

Boundary rules define the lower and upper limits of strategic resilience performance.

Table A17. Boundary rules for Layer L_4.

Rule ID	C_{41}	C_{42}	C_{43}	Output L_4
L4-R1	VL	VL	VL	VL
L4-R2	L	L	L	L
L4-R3	M	M	M	M
L4-R4	H	H	H	H
L4-R5	VH	VH	VH	VH

Appendix A.4.2. Governance-Dominance Rules for Layer L_4

These rules reflect the assumption that resilience governance maturity acts as the institutional backbone of strategic resilience. Weak governance structures limit the effectiveness of planning and collaboration initiatives.

Table A18. Governance-dominance rules for Layer L_4.

Rule ID	C_{41}	C_{42}	C_{43}	Output L_4
L4-R6	VL	H	H	M
L4-R7	VL	VH	VH	M
L4-R8	VL	M	M	L
L4-R9	L	H	H	M
L4-R10	L	VH	VH	H
L4-R11	H	M	M	M
L4-R12	VH	M	M	H
L4-R13	VH	H	H	VH

The above rules capture the notion that strategic resilience requires institutional support structures and governance mechanisms to transform plans into effective actions.

Appendix A.4.3. Planning-Dominance Rules for Layer L_4

These rules emphasize the importance of resilience-oriented planning in preparing organizations for future disruptions.

Table A19. Planning-dominance rules for Layer L_4.

Rule ID	C_{41}	C_{42}	C_{43}	Output L_4
L4-R14	H	VL	H	M
L4-R15	VH	VL	VH	M
L4-R16	M	VL	M	L
L4-R17	H	L	H	M
L4-R18	VH	L	VH	H
L4-R19	M	H	M	M
L4-R20	H	VH	H	H

These rules reflect the assumption that resilience planning translates strategic intent into actionable preparedness measures, including contingency planning, disruption scenarios, and resilience investment priorities.

Appendix A.4.4. Collaboration-Dominance Rules for Layer L_4

These rules represent situations in which strategic resilience is influenced by the quality of relationships within the supply network.

Table A20. Collaboration-dominance rules for Layer L_4.

Rule ID	C_{41}	C_{42}	C_{43}	Output L_4
L4-R21	H	H	VL	M
L4-R22	VH	VH	VL	M
L4-R23	M	M	VL	L
L4-R24	H	H	L	M
L4-R25	VH	VH	L	H

These rules reflect the premise that resilience increasingly depends on inter-organizational cooperation, information sharing, trust, and coordinated response mechanisms.

Appendix A.4.5. Strategic Excellence Scenarios for Layer L_4

The final group contains configurations representing highly resilient strategic systems characterized by strong governance, proactive planning, and advanced collaboration capabilities.

Table A21. Strategic excellence scenarios for Layer L_4.

Rule ID	C_{41}	C_{42}	C_{43}	Output L_4
L4-R26	VH	VH	H	VH
L4-R27	VH	H	VH	VH
L4-R28	H	VH	VH	VH
L4-R29	VH	H	H	VH
L4-R30	H	VH	H	VH

These rules represent organizations that have successfully institutionalized resilience principles, integrated resilience into strategic planning processes, and established strong collaborative ecosystems capable of supporting long-term adaptation and recovery.

The final Layer L_4 rule base consists of **30 rules**, organized into five complementary categories.

Table A22. Strategic excellence scenarios for Layer L_4.

Rule Category	Number of Rules
Boundary rules	5
Governance-dominance rules	8
Planning-dominance rules	7
Collaboration-dominance rules	5
Strategic excellence scenarios	5
Total	30

The resulting rule base captures the essential strategic mechanisms governing long-term resilience while maintaining a manageable level of complexity. Together with the fuzzy inference mechanism, these rules provide a transparent and reproducible representation of strategic resilience formation within procurement and supply chain systems.

Appendix A.5. System-Level Aggregation Rule Base

The final stage of the FHOR-RAM model aggregates the resilience scores obtained for the four House of Resilience layers into a single overall resilience assessment. This aggregation represents the highest level of the hierarchical fuzzy inference system and reflects the systemic nature of resilience, where structural, operational, technological, and strategic capabilities jointly determine the organization's ability to withstand and recover from disruptions. The aggregation layer is defined by the following inputs:

- L_1: Technological and risk assessment,
- L_2: Operational and adaptive resilience,
- L_3: Structural resilience,
- L_4: Strategic resilience.

The output variable is:

- R_{HoR}: Overall House of Resilience score.

The complete theoretical rule space contains $N_{RHoR} = 5^4 = 625$ possible rule combinations. Following the reduction methodology described in Section 5.4.3, a representative rule base consisting of 48 rules is employed. The rule base is designed to preserve the fundamental assumptions of the House of Resilience framework while ensuring computational tractability and interpretability.

The aggregation logic is based on four key assumptions:

1. Structural resilience (L_3) acts as the foundation of the system and therefore exerts the strongest influence on overall resilience.
2. Strategic resilience (L_4) determines long-term sustainability and preparedness.
3. Technological resilience (L_1) enables visibility, risk awareness, and informed decision-making.
4. High resilience requires balanced development across all layers; severe weaknesses cannot be fully compensated by strengths elsewhere.

The final rule base is organized into six groups.

To further preserve the non-compensatory nature of resilience and ensure consistency with the House of Resilience philosophy, additional mixed-condition rules were introduced. These rules capture situations where multiple layers simultaneously exhibit low resilience levels. In such configurations, the overall resilience assessment is intentionally constrained, preventing unrealistically high system-level outputs that could otherwise emerge from compensation effects during fuzzy interpolation. This extension improves the consistency between layer-level and system-level assessments and strengthens the diagnostic interpretability of the model.

Appendix A.5.1. Boundary Rules

Boundary rules define the minimum and maximum limits of system resilience.

Table A23. Boundary rules.

Rule ID	L_1	L_2	L_3	L_4	R_{HoR}
S-R1	VL	VL	VL	VL	VL
S-R2	L	L	L	L	L
S-R3	M	M	M	M	M
S-R4	H	H	H	H	H
S-R5	VH	VH	VH	VH	VH

Appendix A.5.2. Structural Dominance Rules (L_3)

These rules reflect the assumption that structural resilience forms the foundation of the House of Resilience. Weak structural conditions limit the effectiveness of all other layers.

These rules operationalize the non-compensatory role of structural robustness within the HoR framework.

Table A24. Structural dominance rules.

Rule ID	L_1	L_2	L_3	L_4	R_{HoR}
S-R6	H	H	VL	H	M
S-R7	VH	VH	VL	VH	M
S-R8	H	H	L	H	M
S-R9	VH	VH	L	VH	M
S-R10	M	M	VL	M	L
S-R11	H	M	VL	H	M
S-R12	M	H	VL	H	M
S-R13	VH	H	L	H	M
S-R14	H	VH	L	VH	M
S-R15	VH	VH	M	VH	H
S-R16	L	M	L	L	L/M
S-R17	L	H	L	L	L
S-R18	M	M	L	L	M
S-R19	L	H	L	L	M

Appendix A.5.3. Strategic Deficiency Rules (L_4)

The following rules capture situations where insufficient strategic governance and planning constrain overall resilience.

Table A25. Strategic deficiency rules.

Rule ID	L_1	L_2	L_3	L_4	R_{HoR}
S-R20	H	H	H	VL	M
S-R21	VH	VH	VH	VL	M
S-R22	H	H	H	L	M
S-R23	VH	VH	VH	L	H
S-R24	M	M	M	VL	M
S-R25	L	M	M	L	M
S-R26	M	H	M	L	M

These rules emphasize the importance of long-term resilience governance and planning.

Appendix A.5.4. Technology Deficiency Rules (L_1)

These rules reflect situations where limited digitalization, visibility, and risk awareness reduce the effectiveness of other resilience capabilities.

Table A26. Technology deficiency rules.

Rule ID	L_1	L_2	L_3	L_4	R_{HoR}
S-R27	VL	H	H	H	M
S-R28	VL	VH	VH	VH	M
S-R29	L	H	H	H	M
S-R30	L	VH	VH	VH	H
S-R31	VL	M	M	M	L
S-R32	L	M	M	M	M
S-R33	L	H	M	M	M

Although technology is not considered foundational, severe technological deficiencies reduce resilience by limiting visibility and response capabilities.

Appendix A.5.5. Balanced Resilience Scenarios

Balanced scenarios represent realistic situations in which resilience levels are relatively consistent across layers.

Table A27. Balanced scenarios.

Rule ID	L_1	L_2	L_3	L_4	R_{HoR}
S-R34	M	M	H	M	M
S-R35	M	H	M	M	M
S-R36	H	M	M	M	M
S-R37	M	M	M	H	M
S-R38	H	H	M	M	H
S-R39	H	M	H	M	H
S-R40	M	H	H	M	H
S-R41	M	M	H	H	H
S-R42	H	H	H	M	H
S-R43	M	H	H	H	H

These rules describe the most common operational states expected in real procurement systems.

Appendix A.5.6. Excellence Scenarios

The final group represents highly resilient systems exhibiting strong performance across all House of Resilience layers.

Table A28. Excellence scenarios.

Rule ID	L_1	L_2	L_3	L_4	R_{HoR}
S-R44	VH	VH	VH	H	VH
S-R45	VH	VH	H	VH	VH
S-R46	VH	H	VH	VH	VH
S-R47	H	VH	VH	VH	VH
S-R48	VH	VH	H	H	H

These rules represent organizations that simultaneously exhibit strong technological capabilities, adaptive operational performance, robust structural foundations, and mature strategic governance.

The final system-level aggregation rule base consists of 48 rules according to Table A29.

Table A29. Rule base configuration for system-level.

Rule Category	Number of Rules
Boundary rules	5
Structural dominance rules	14
Strategic deficiency rules	7
Technology deficiency rules	7
Balanced scenarios	10
Excellence scenarios	5
Total	48

The resulting aggregation mechanism preserves the conceptual logic of the House of Resilience framework while ensuring transparency, reproducibility, and computational efficiency. Together with the layer-level rule bases, it provides a complete fuzzy inference structure enabling the assessment of overall procurement resilience through the FHOR-RAM model.

Appendix A.6. Reproducibility Statement

The complete fuzzy rule bases reported in this appendix provide a transparent specification of the inference logic implemented in the FHOR-RAM model using the MATLAB Fuzzy Logic Toolbox. Together with:

- the linguistic variables defined in Section 5.3,
- the membership functions,
- the Mamdani inference mechanism,
- and the rule bases presented herein,

The proposed model can be fully reconstructed and replicated by other researchers.

Appendix B. Detailed Rule Base for Layer L_3 (Structural Resilience)

Layer L_3 represents the foundational resilience of the procurement system and is defined by three criteria:

- C_{31}: Supplier diversification,
- C_{32}: Lead time stability,
- C_{33}: Critical material availability,

The rule base for this layer is constructed to reflect the non-compensatory nature of structural resilience, where severe weakness in any critical dimension may significantly degrade the overall layer performance. At the same time, moderate compensation is allowed for mid-level conditions.

To ensure both interpretability and sufficient coverage of the input space, a reduced but explicit rule base consisting of 30 rules (approximately 24% of the theoretical rule space) is defined (Table A30). This rule base captures:

- extreme conditions (failure/success),
- majority-driven scenarios,
- mixed configurations,
- dominance of critical weaknesses.

The rule design follows four fundamental principles that ensure interpretability, logical consistency, and behavioral completeness of the fuzzy inference system. First, the principle of dominance of worst-case conditions assumes that the presence of *Very Low* (*VL*) values across multiple input criteria significantly reduces the overall resilience level, reflecting the system's sensitivity to critical weaknesses. Second, the majority-based evaluation principle ensures that the output resilience level is primarily determined by the dominant linguistic state among the inputs, supporting a form of consensus-driven inference. Third, the balanced configurations principle states that homogeneous input conditions (i.e., all inputs at the same linguistic level) directly map to the corresponding output level, preserving structural symmetry in the rule base. Finally, the limited compensation principle allows higher input values to partially offset medium conditions; however, this compensatory effect is strictly constrained and cannot override the influence of *Very Low* or strongly adverse conditions.

The interpretation of the rule structure can be grouped into distinct resilience regions. Rules R1–R4 define the critical failure zone, where multiple Very Low inputs lead to a Very Low resilience outcome, capturing severe structural fragility. Rules R5–R11 represent the low resilience zone, where the presence of at least one Very Low condition combined with generally weak input states results in an overall low resilience assessment. Rules R12–R18 correspond to the moderate resilience zone, characterized by balanced or mixed Medium input configurations that yield a medium level of resilience. In contrast, Rules R19–R22 define the high resilience zone, where a majority of High inputs leads to strong structural robustness. Rules R23–R29 capture the very high resilience zone, in which dominance of

Very High inputs results in top-level resilience performance. Finally, Rule R30 formalizes a specific compensation mechanism, whereby a Very High input may partially offset medium-level conditions; however, this compensatory effect remains limited and does not extend to low or very low states.

The adoption of a reduced rule base inevitably involves a trade-off between completeness and model tractability. However, the reduction strategy applied in this study is designed to minimize information loss by preserving all boundary conditions, representative intermediate states, and dominant resilience patterns. Since the Mamdani inference mechanism operates on overlapping fuzzy sets rather than discrete categories, the system is capable of interpolating between explicitly defined rules. Consequently, input combinations not directly represented in the rule base are evaluated through partial activation of neighboring rules, producing smooth and continuous output responses. This property substantially reduces the risk of inference bias associated with rule reduction. Furthermore, the retained rules were selected to cover the most decision-relevant regions of the input space, ensuring that the resulting resilience scores remain consistent with the theoretical assumptions of the HoR framework and established resilience principles.

Table A30. Complete rule base for Layer L_3.

Rule ID	C_{31}	C_{32}	C_{33}	Output L_3	Rule ID	C_{31}	C_{32}	C_{33}	Output L_3
R1	VL	VL	VL	VL	**R16**	H	M	M	M
R2	VL	VL	L	VL	**R17**	M	H	M	M
R3	VL	L	VL	VL	**R18**	M	M	H	M
R4	L	VL	VL	VL	**R19**	H	H	M	H
R5	VL	L	L	L	**R20**	H	M	H	H
R6	L	VL	L	L	**R21**	M	H	H	H
R7	L	L	VL	L	**R22**	H	H	H	H
R8	L	L	L	L	**R23**	VH	H	H	VH
R9	VL	M	M	L	**R24**	H	VH	H	VH
R10	M	VL	M	L	**R25**	H	H	VH	VH
R11	M	M	VL	L	**R26**	VH	VH	H	VH
R12	L	M	M	M	**R27**	VH	H	VH	VH
R13	M	L	M	M	**R28**	H	VH	VH	VH
R14	M	M	L	M	**R29**	VH	VH	VH	VH
R15	M	M	M	M	**R30**	VH	M	M	H

Overall, the proposed rule base provides effective coverage of the relevant behavioral space of the system, ensuring smooth transitions between resilience levels while maintaining interpretability and avoiding unnecessary redundancy. Although the rule base does not explicitly enumerate all possible input combinations, the use of overlapping fuzzy membership functions and Mamdani inference enables continuous approximation across the entire input domain.

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