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Generative AI as a Cognitive Orchestration Capability for Supply Chain Resilience: A Conceptual Framework

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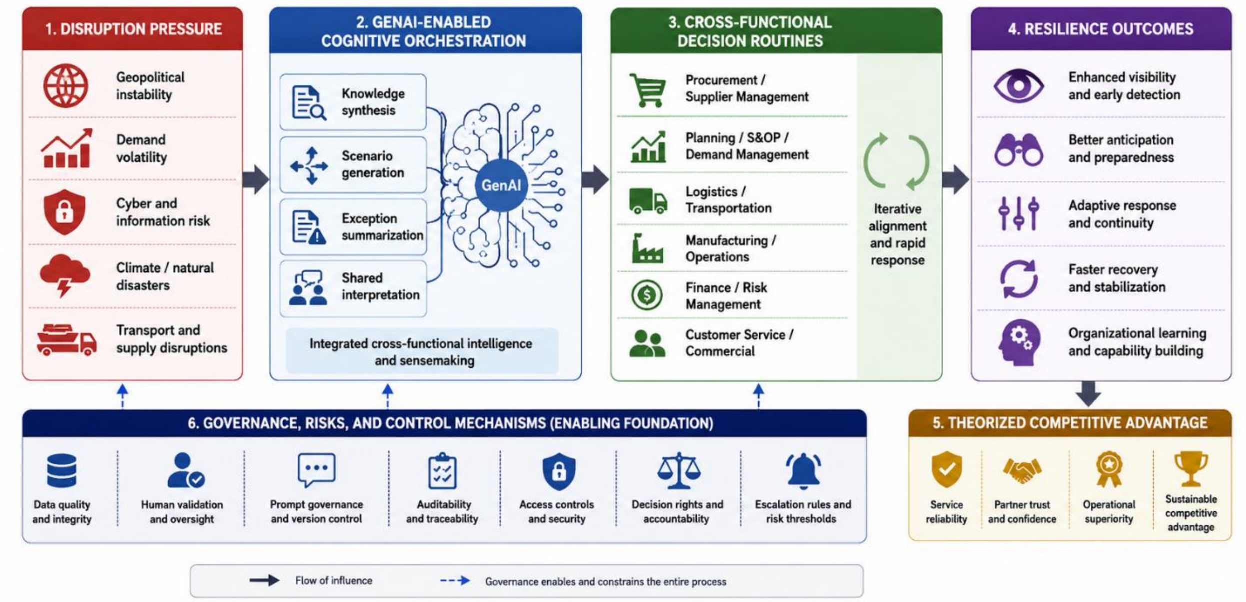
Graphical Abstract



ABSTRACT

Resilience in the context of the supply chain has emerged as a crucial strategic issue, given the various disruptions arising due to geopolitical instabilities, climatic disturbances, vulnerabilities to cyber-attacks, logistical issues, and fluctuating demand. While there is increasing interest in using artificial intelligence in supply chain management research, most discussions on the topic center around applying AI to specific functional tasks like forecasting, procurement, logistics management, and operations. In contrast, this paper attempts to answer the following question: What role can Generative Artificial Intelligence play in enabling cross-functional interpretation and decision-making during disruptions? Building on the resource orchestration theory, dynamic capabilities and organizational information processing theory, the paper proposes the construct of GenAI-enabled cognitive orchestration. Cognitive orchestration can be defined as the governance of the use of GenAI for integrating dispersed organizational knowledge, decision processes, and responses across supply chain functions under conditions of uncertainty. The theoretical perspective underlying this research builds on a systematic literature review. The theory goes on to postulate that these results are contingent on the following: data integrity, human validation, timely governance, audibility, cross-functional trust, and decision-making rights clarity. This research makes a contribution in terms of differentiating between cognitive

orchestration and some other constructs, including AI-based decision support, analytics capabilities, digital control tower, digital twin, and overall cross-functional integration. Finally, this work proposes propositions for future research as well as prescribes some governance guidance regarding the use of GenAI as orchestration technology.
Keywords: *Generative artificial intelligence; cognitive orchestration; supply chain resilience; cross-functional integration; dynamic capabilities; resource orchestration; organizational information processing; AI governance.*

1. Introduction

Supply chains are faced with multiple and simultaneous disruptions from geopolitics, climate changes, transportation challenges, cybersecurity threats, and fluctuating consumer demand. In light of such challenges, resilience can no longer be viewed as a mere operational insurance; instead, it is necessary for continuity, integrity, and sustained competitiveness. Past literature on supply chain management has found that companies are able to survive the effects of disruptions not only due to their resource base but because they have established an appropriate mix of visibility, flexibility, cooperation, and preparedness to recover and adjust (Christopher & Peck, 2004; Pettit et al., 2010; Ambulkar et al., 2015). More contemporary views recognize resilience as a dynamic ability that involves anticipating and responding to challenges, as well as recovering and adjusting (Duchek, 2020; Song et al., 2022). Artificial intelligence has also become an important technological trajectory in supply chain management. Recent studies show that AI research in SCM has moved beyond general technological optimism toward concrete applications in forecasting, procurement, logistics, planning, risk detection, and operational optimization (Culot et al., 2024; Ferreira et al., 2025). This literature has contributed substantially to understanding how AI can improve specific supply chain tasks. However, much of the existing discussion remains function-specific. Demand-planning studies often emphasize forecasting accuracy, procurement studies focus on supplier evaluation or sourcing support, and logistics studies frequently examine routing, visibility, or exception management. These applications are valuable, but they do not fully address the cross-functional nature of disruption response.

This limitation is theoretically and managerially important because supply chain disruptions rarely remain confined to one function. A supplier failure may simultaneously affect production schedules, transport plans, customer commitments, inventory allocation, financial exposure, and risk communication. In such conditions, resilience depends not only on analytical accuracy within individual functions, but also on the organization's capacity to connect distributed knowledge, reconcile competing priorities, and coordinate timely response actions across functional boundaries. The central question is therefore not simply whether AI can improve a forecast, automate a report, or accelerate local decision support. The more important question is how AI can support shared interpretation and coordinated decision-making when disruption creates uncertainty across multiple supply chain functions. Generation artificial intelligence makes decision-making within a digital supply chain even more likely both for the opportunities and risks that are associated with its use. As opposed to previous decision support technologies, GenAI has a number of advantages, which allow making it useful for cross-functional resilience. For example, it is able to combine structured and unstructured data, detect and summarize exceptions, suggest various scenarios, provide comparison of various options, make trade-off analysis, and communicate using natural language with humans. At the same time, the effectiveness of all these functions is dependent on the quality of available data, its retrieval and grounding process, prompt development, human verification, role-based access control, and proper decision-making governance.

This paper addresses this theoretical and managerial gap through the concept of cognitive orchestration. Cognitive orchestration refers to the purposeful use of GenAI to connect distributed organizational knowledge, decision routines, and response actions across supply chain functions. It is cognitive because it supports sensing, interpretation, scenario generation, judgment preparation, and collective learning. It is orchestration because value emerges from the managerial alignment of data, people, workflows, decision rights, and governance mechanisms rather than from model deployment alone. This concept positions GenAI not as a stand-alone automation tool, but as a socio-technical coordination capability embedded in governed cross-functional decision processes. In order to elaborate on this theory, the paper draws on three theories including Resource Orchestration Theory, Dynamic Capabilities, and Organizational Information Processing Theory. Resource Orchestration Theory helps explain how organization's structure and bundle resources into capabilities (Sirmon et al., 2011). The Dynamic Capabilities framework describes the ability of organizations to recognize threats, identify and act upon responses, and restructure their resources to respond (Teece, 2007). The Organizational Information Processing Theory provides an understanding of the increased need for information-processing ability under uncertainty (Galbraith, 1974). Collectively, these theoretical perspectives can be used to understand the potential of GenAI for supply chain resilience through governed activities across functions.

The paper makes three contributions. First, it defines GenAI-enabled cognitive orchestration as a bounded conceptual construct and distinguishes it from adjacent ideas such as AI decision support, analytics capability, digital control towers, digital twins, and general cross-functional integration. Second, it explains the mechanisms through which GenAI may support resilience by structuring cross-functional intelligence resources, bundling them into recurring decision routines, and leveraging them for adaptive response, recovery , and learning. Third, it theorizes the governance and organizational conditions under which resilience gains may contribute to competitive advantage, while also identifying risks such as hallucination, overreliance, data leakage, interpretive conflict, and unclear decision authority. The study is guided by three research questions: RQ1: How can GenAI be conceptualized as a cognitive orchestration capability in supply chains? RQ2: Through which cross-functional mechanisms may GenAI strengthen supply chain resilience? RQ3: Under what governance and organizational conditions may resilience gains contribute to competitive advantage?

The rest of the paper is organized in the following way. In section two, the theoretical foundations for and the boundaries of the construct of cognitive orchestration will be developed. In section three, the approach employed and its logic for building the theory will be presented. In section four, the conceptual framework and the propositions will be developed. In section five, theoretical implications, boundary conditions, and managerial implications will be discussed.

2. Theoretical Foundations and Construct Boundaries

This section develops the theoretical foundation for conceptualizing GenAI-enabled cognitive orchestration in supply chains. Three theoretical lenses are used because each explains a different part of the problem. Resource Orchestration Theory explains how resources become capabilities through managerial structuring, bundling, and leveraging. Dynamic Capabilities explain how firms sense threats, seize response opportunities, and reconfigure resources under disruption. Organizational Information Processing Theory explains why uncertainty increases the need for richer information-processing capacity and cross-functional coordination. Together, these perspectives provide a basis for theorizing GenAI not as an isolated digital tool, but as a governed socio-technical capability that may support resilience when embedded in cross-functional decision routines.

2.1 Resource Orchestration Theory

Resource Orchestration Theory argues that resources do not create advantage automatically. Strategic value depends on how managers structure, bundle, and leverage resources into productive capability configurations (Sirmon et al., 2011). Structuring involves acquiring, organizing, and governing relevant resources. Bundling refers to combining resources into coherent capabilities through stabilization, enrichment, and renewal. Leveraging concerns the deployment of those capabilities toward strategic objectives. This perspective is especially relevant for digital transformation because advanced technologies often fail to generate value when they remain disconnected from organizational routines, decision rights, and managerial action. Applied to GenAI in supply chains, Resource Orchestration Theory shifts attention away from model acquisition and toward the managerial design of intelligence architecture. A firm may possess enterprise data, supplier records, planning systems, operational alerts, and collaborative platforms, but these resources remain strategically weak if they are fragmented across functions or disconnected from decision routines. The theory comes into play when managers employ GenAI to organize cross-functional information resources, bundle them with domain knowledge and routine processes, and harness them for coordinated response to uncertainties. In other words, cognitive orchestration is not about the capabilities of GenAI; it is rather about how managers manage GenAI-enabled knowledge aggregation within the context of cross-functional decision-making and resource allocation. The distinction is essential because the problem at hand is not just about information accessibility. Firms experiencing disruptions need to prioritize among the signals, functions, decisions, and resource allocations required to respond to the situation. GenAI can potentially support these activities by synthesizing disparate inputs into unified outputs in the form of summaries, scenarios, and narratives. The usefulness of these outputs depends, however, on embedding them into routines that allow for connecting information with power and action and the Resource Orchestration Theory thus offers the first basis for the paper.

2.2 Dynamic Capabilities and Resilience

The Dynamic Capability Theory describes how firms react to change through the process of sensing, seizing, and reconfiguration (Teece, 2007). The theory fits perfectly into the context of supply chain resilience since resilience requires more than robustness. A resilient firm must foresee disruptions, withstand disruptions, coordinate responses, restore its functionality, and gain experience from disruptive events. Resilience, in other words, is a dynamic capability which entails interpretation, coordination, and adaptation over time (Duchek, 2020). In the limited sense, GenAI can be used for developing microfoundations for dynamic capabilities. It could enable sensing by aggregating fragmented information from suppliers, logistics providers, customer demands, services, media outlets, and internal exception reports. It could help with seizing through generating response scenarios and facilitating coordination among different functions at decision-making meetings. It could facilitate reconfiguration by assisting managers in comparing resource-allocation options, explaining response decisions, accessing previous disruption management playbooks, and translating lessons learned into procedural knowledge. These roles make GenAI potentially relevant to resilience, but they do not imply automatic performance improvement. The dynamic capability value of GenAI depends on whether AI-supported interpretation can be translated into timely action. If managers lack reconfiguration authority, if functions disagree on priorities, or if outputs are not validated, GenAI may produce decision noise rather than resilience. Cognitive orchestration is therefore conceptualized as a conditional pathway. It links GenAI-supported cognition to resilience only when firms possess the governance, integration, and managerial authority required to convert intelligence into adaptive response. Dynamic Capabilities provide the second foundation for the paper: GenAI may support resilience by strengthening sensing, seizing, and reconfiguring, but only when embedded in organizational processes capable of action.

2.3 Cross-Functional Integration and Organizational Information Processing

Supply chain disruptions generate more uncertainty, ambiguity, and stress. According to Organizational Information Processing Theory, organizations operating under uncertainty have to either lower the demands of information processing or enhance their information-processing capability (Galbraith, 1974). With supply chain operations, disruption often generates higher demands for information-processing due to decisions needing to be made regarding procurement, production, logistics, marketing, finance, customer service, as well as other business processes and partners. Specialization by function builds competency, but it may lead to problems such as information asymmetry, local optimization, delayed escalations, and varied interpretations of similar events. Cross-functional integration is critical for building resiliency capabilities. Several studies confirm that information collection and information sharing contribute to building resiliency only in cases where organizational functions are integrated and able to coordinate their interpretation and responses (van den Adel et al., 2023). These insights are important for GenAI because the technology may expand access to information without improving decision quality. If different functions use inconsistent data sources, prompt templates, assumptions, or performance criteria, GenAI may accelerate fragmentation rather than reduce it. Cognitive orchestration addresses this problem by treating GenAI as a coordination medium rather than as a local decision aid. Its value lies in helping organizations create shared situational awareness, translate specialized knowledge across functions, generate comparable response options, and support collective judgment under uncertainty. From an Organizational Information Processing perspective, GenAI may increase information-processing capacity by converting dispersed information into decision-ready narratives. From a cross-functional integration perspective, those narratives matter only when they are embedded in routines that reconcile trade-offs and clarify decision rights. These perspectives provide the third foundation for the paper: GenAI-enabled resilience depends on shared interpretation and coordinated action, not merely on faster information production.

2.4 Distinguishing Cognitive Orchestration from Adjacent Constructs

Cognitive orchestration, in turn, can be understood as intentional application of GenAI for connecting distributed organizational knowledge, decision-making procedures, and action routines in conditions of uncertainty within the supply chain management process. This construct is called cognitive due to its support for cognitive processes such as sensing, interpretation, scenario development, judgment preparation, and collective learning. Orchestration means that value arises from managerial alignment of data, people, processes, governance and decision power. Thus, cognitive orchestration cannot be understood as either GenAI adoption per se or digital transformation as an overarching concept. Instead, it should be treated as managed application of GenAI as a coordination capacity. Cognitive orchestration is related to several well-known concepts but cannot be reduced to them. AI-driven decision support usually helps resolve bounded tasks by means of recommendations, scores, forecasts, or alerts. Analytics capability stands for organizational capabilities to collect, analyze, and leverage data. Control towers represent efforts towards increased visibility and situational awareness of events. Digital twins deal with virtual representations and simulations of operational systems. Cognitive orchestration should not be used as a new label for any AI tool in supply chain management. It applies only where GenAI is used to integrate distributed knowledge, support shared interpretation, and connect decision preparation with cross-functional response. A forecasting model used only by demand planners would not constitute cognitive orchestration. A chatbot answering routine procurement questions would not constitute cognitive orchestration. A dashboard displaying logistics events would not constitute cognitive orchestration. By contrast, a governed GenAI-enabled routine that synthesizes supplier alerts, production constraints, inventory exposure, customer priorities, and financial implications into validated response scenarios for a cross-functional disruption meeting would represent cognitive orchestration. This definition establishes the construct's theoretical boundaries and supports the proposition development that follows. Cognitive orchestration is positioned as a conditional capability: it may strengthen supply chain resilience when GenAI-supported knowledge synthesis is governed, cross-functional, validated, and connected to resource reconfiguration authority. Without these conditions, GenAI may remain a local productivity tool or, worse, amplify inconsistent interpretations and false confidence across functions. Also, Table 1 currently contains constructs such as AI decision support, analytics capability, digital control tower, digital twin, and cross-functional integration, but the table itself has no visible citations. If you keep references such as Duan et al. (2019), Arunachalam et al. (2018), Patsavellas et al. (2021), Ivanov and Dolgui (2021), Waller and Fawcett (2013), and Kahn and Mentzer (1998), cite them in Table 1 or in the paragraph before it. Otherwise, they will look uncited.

Table 1: Construct boundaries of GenAI-enabled cognitive orchestration.

Construct	Primary focus	Typical output	Boundary from cognitive orchestration
AI decision support	Assisting a bounded task or decision	Recommendation, prediction, score, alert, or ranking	Usually task-specific and function-local. Cognitive orchestration focuses on cross-functional interpretation, response preparation, and coordinated action during disruption.
Analytics capability	Organizational capacity to collect, process, analyze, and use data	Dashboards, forecasts, optimization results, performance indicators	Emphasizes analytical capacity broadly. Cognitive orchestration adds GenAI-mediated synthesis, translation, scenario narration, and shared decision preparation across functions.
Digital control tower	End-to-end monitoring and visibility across supply chain events	Real-time alerts, status updates, exception visibility, operational dashboards	Visibility is necessary but insufficient. Cognitive orchestration uses visibility as input for shared interpretation, trade-off reconciliation, and cross-functional response coordination.

Digital twin	Virtual representation and simulation of assets, processes, or networks	What-if simulations, scenario models, operational replicas	Simulation can inform orchestration, but cognitive orchestration additionally concerns who interprets outputs, validates assumptions, and converts scenarios into governed cross-functional decisions.
Cross-functional integration	Alignment of internal functions through communication, collaboration, and shared processes	Better coordination, information sharing, and joint planning	A broader organizational capability. Cognitive orchestration is a GenAI-enabled extension that specifically supports distributed knowledge synthesis, decision preparation, and response coordination under uncertainty.
GenAI-enabled cognitive orchestration	Governed use of GenAI to connect distributed knowledge, decision routines, and response actions across supply chain functions	Shared disruption narratives, validated scenarios, exception summaries, trade-off options, response briefs, learning artifacts	Distinctive because it combines GenAI-mediated interpretation with cross-functional routines, human validation, governance controls, and resource reconfiguration authority.

3. Methodological Approach

This paper adopts a theory-building conceptual design supported by a structured literature review. The purpose is not to estimate empirical effect sizes or provide an exhaustive bibliometric mapping of GenAI in supply chain management. Rather, the objective is to develop a transparent conceptual base for theorizing how GenAI-enabled cognitive orchestration may support supply chain resilience through cross-functional decision-making. This approach is appropriate because the focal phenomenon remains emerging, theoretically underdeveloped, and insufficiently validated through large-scale empirical research. The review therefore serves as a theory-building device: it identifies relevant literature streams, clarifies construct boundaries, supports mechanism development, and informs the proposition set advanced in Section 4.

3.1 Research Design

The paper takes a conceptual approach in the form of theory building. Primary data such as survey data, interviews, archival data, and experimentation were not conducted. Rather, the purpose of this paper is to create a framework that will link well-established theoretical perspectives to recent studies related to artificial intelligence, generative artificial intelligence (GenAI), resilience in the supply chain, cross-functional integration, and governance. It is not the intention of this paper to examine whether the use of GenAI currently enhances resilience but rather to provide the context within an organization whereby GenAI may act as a cross-functional orchestration capability. The outputs of this design are a bounded construct definition, theoretical mechanisms, and propositions. Three theoretical perspectives are employed within this research paper. Resource Orchestration Theory will explain how GenAI-related resources may be structured, packaged, and used as organizational capabilities. Dynamic Capabilities Theory will explain the role of GenAI-enabled cognition in the sensing, seizing, and reconfiguration process in times of disruption. Organizational Information Processing Theory will explain the rationale for disruption increasing information processing needs and the importance of cross-functional coordination.

3.2 Structured Literature Review Strategy

The review addressed four overlapping areas of literature, which include resilience in the supply chain, cross functional integration, use of AI in SCM, and governance/oversight of GenAI. For contemporary literature review, the timeline included publications between 2020 and 2026 on matters concerning AI and GenAI. However, in defining theories like Resource Orchestration Theory, Dynamic Capabilities, Organizational Information Processing Theory, and fundamentals of supply chain resilience, older literature was employed. The literature review employed Scopus and Web of Science as primary sources for information discovery; Emerald, Wiley, Springer, Science Direct, and Taylor & Francis were utilized for verification purposes. Searches were performed using the article title, abstract, and keyword searches; backward reference checking was done for seminal papers in theory and resilience literature. Representative search clusters included GenAI or large language models and supply chain management; artificial intelligence and procurement, logistics, planning, forecasting, or risk management; dynamic capabilities and supply chain resilience; cross-functional integration and information processing; and AI governance, human oversight, auditability, or accountability in organizational decision-making. The review is deliberately positioned as structured and theory-building rather than exhaustive. It does not claim PRISMA-style completeness, bibliometric coverage, or quantitative synthesis. This positioning is important because the aim is conceptual development rather than systematic estimation of a literature population.

3.3 Inclusion, Exclusion, and Screening Logic

The sources were selected on the basis of their direct contribution to at least one of the major concepts covered by the paper: supply chain resilience, AI/GenAI in SCM, cross-functional collaboration, information processing within an organization, resource orchestration, dynamic capabilities, or governance of AI. Preference was given to peer-reviewed journal papers, highly cited theories, systematic reviews, and well-designed research papers with a practical focus on organizational decision making. The sources that did not make any theoretical or empirical contributions but merely outlined technical aspects of the models and had no managerial or SCM implications were excluded. Vendor-sponsored reports, anonymous papers, magazines, and unreviewed sources were not taken into consideration. Similarly, practitioner sources were not used to support theoretical propositions unless they were necessary for contextual understanding and could be separated from the academic evidence base. The screening logic followed three stages. First, titles and abstracts were reviewed for topical fit with the focal literature streams. Second, full texts were assessed for relevance to the mechanisms of resilience, orchestration, cross-functional coordination, governance, and decision support. Third, retained sources were interpreted concept-centrically to identify how they informed the framework dimensions. Table 2 summarizes the structured review protocol and screening criteria used to support the theory-building process.

Table 2. Structured review protocol

Component	Specification

Review objective	To identify the literature streams needed to theorize GenAI-enabled cognitive orchestration for supply chain resilience and to clarify the governance conditions shaping its effects.
Review design	Structured, concept-centric, and theory-building review rather than an exhaustive PRISMA-style systematic review.
Core literature streams	Supply chain resilience; AI and GenAI in supply chain management; cross-functional integration; Resource Orchestration Theory; Dynamic Capabilities; Organizational Information Processing Theory; AI governance and human oversight.
Search refinement date	14 June 2026.
Main discovery databases	Scopus and Web of Science.
Source verification platforms	Emerald, Wiley, Springer, ScienceDirect, Taylor & Francis, and other publisher databases where needed for full-text access and bibliographic verification.
Search fields	Title, abstract, and keywords, supplemented by backward reference chaining for seminal theory and resilience papers.
Contemporary search window	2020–2026 for AI, GenAI, digital supply chain, and governance-related studies.
Foundational sources	Earlier seminal sources were retained where necessary for Resource Orchestration Theory, Dynamic Capabilities, Organizational Information Processing Theory, cross-functional integration, and supply chain resilience foundations.
Representative search clusters	“Generative AI” OR “large language model*” AND “supply chain”; “artificial intelligence” AND “supply chain resilience”; “dynamic capability*” AND “supply chain resilience”; “cross-functional integration” AND “information processing”; “AI governance” OR “human oversight” OR “auditability” AND “decision-making.”
Inclusion criteria	English-language peer-reviewed journal articles, influential theory papers, systematic reviews, and high-quality conceptual or empirical studies relevant to supply chain resilience, AI/GenAI in SCM, cross-functional integration, governance, information processing, or decision-making.
Exclusion criteria	Vendor reports, magazine articles, anonymous white papers, promotional material, purely technical algorithm papers without managerial relevance, non-English publications not accessible for consistent interpretation, and sources lacking scholarly review or contribution transparency.
Screening logic	Sources were screened first for topical fit, then for full-text relevance to orchestration, resilience, cross-functional coordination, governance, and decision support.
Review output	Construct boundaries, framework dimensions, governance conditions, and propositions for future empirical testing.

3.4 Concept-Centric Coding and Synthesis

The synthesis followed a concept-centric logic rather than an author-by-author summary. During first-cycle coding, studies were tagged according to domain focus, technology role, organizational mechanism, and outcome type. Domain focus included procurement, planning, logistics, operations, customer service, risk management, and post-disruption learning. Technology role included analytics, automation, decision support, GenAI interface, scenario generation, and knowledge synthesis. Organizational mechanisms included visibility, information sharing, cross-functional integration, collaboration, learning, flexibility, governance, and escalation. Outcome types included resilience, response speed, recovery, adaptation, performance, trust, and competitive implications. During second-cycle coding, these categories were consolidated into higher-order themes aligned with the theoretical framework. Shared data definitions, enterprise knowledge access, and semantic alignment were grouped under structuring cross-functional intelligence resources. Scenario generation, exception triage, meeting preparation, and precedent retrieval were grouped under bundling GenAI into recurring decision routines. Resource reallocation, trade-off analysis, and post-event documentation were grouped under leveraging cognitive orchestration for resilience outcomes. Service continuity, response credibility, partner confidence, and renewal speed were grouped under the conversion of resilience into competitive advantage. Hallucination risk, data leakage, overreliance, audit gaps, and unclear authority were grouped under governance and contingencies. This synthesis process produced the organizing logic for the conceptual framework. It also ensured that the propositions were not presented as isolated claims, but as relationships derived from the interaction between theoretical lenses and recurring mechanisms in the literature. Table 3 shows how first-cycle codes were consolidated into second-cycle themes and then linked to the framework dimensions used for proposition development.

Table 3. Concept-centric coding and synthesis pathway

First-cycle code	Second-cycle theme	Framework dimension
Shared data definitions; enterprise knowledge access; semantic alignment	Cross-functional intelligence architecture	Structuring intelligence resources
Scenario generation; meeting preparation; exception triage; precedent retrieval	Embedded decision routines	Bundling GenAI into routines
Resource reallocation; cross-functional trade-off analysis; post-event documentation	Coordinated adaptation	Leveraging orchestration for resilience outcomes
Service continuity; partner confidence; response credibility; renewal speed	Strategic consequences of resilience	From resilience to competitive advantage
Hallucination risk; data leakage; overreliance; unclear authority; audit gaps	Socio-technical safeguards	Governance and contingencies

3.5 Methodological Scope and Limitations

The methodological scope of this paper is conceptual. The framework explains theoretically plausible relationships, but it does not empirically test them. The propositions should therefore be interpreted as future research pathways rather than confirmed causal effects. The structured literature review improves transparency and conceptual grounding, but it does not provide an exhaustive systematic review, bibliometric analysis, or meta-analysis. Consequently, the paper does not make claims about publication frequencies, effect sizes, field-wide prevalence, or statistical dominance of particular themes. Several safeguards were used to improve conceptual validity. First, the framework triangulates across resilience scholarship, AI-in-SCM research, cross-functional integration studies, and governance literature instead of relying on a single literature stream. Second, foundational theories are used analytically rather than decoratively; each lens explains a distinct aspect of the framework. Third, the review remains explicit about its limits: no primary data were collected, the propositions are not empirically tested, and the paper does not claim exhaustive systematic-review coverage. These limitations are consistent with the paper's theory-building purpose. The value of the approach lies in clarifying a new construct, specifying its boundaries, identifying mechanisms, and developing testable propositions. Future empirical research should examine the framework through survey designs, comparative case studies, longitudinal disruption-response studies, field experiments, or mixed-method designs. Such research can test whether GenAI-enabled cognitive orchestration improves measurable resilience outcomes such as detection latency, alignment speed, response quality, recovery cycle time, service continuity, and post-disruption learning.

4. Conceptual Framework and Proposition Development

This section develops the conceptual framework and propositions. The framework theorizes GenAI-enabled cognitive orchestration as a layered capability rather than a direct technological effect. Firms first structure cross-functional intelligence resources, then bundle GenAI into recurring decision routines, and finally leverage these routines for adaptive response, recovery, and learning. The framework also treats governance as a constitutive condition rather than a peripheral control mechanism. Without data integrity, human validation, decision-right clarity, and cross-functional integration, GenAI may increase interpretive conflict rather than strengthen resilience. Figure 1 presents the proposed conceptual framework. It links the theoretical foundations developed in Section 2 with the structured review logic explained in Section 3. The framework shows how GenAI-enabled cognitive orchestration may influence resilience outcomes through structuring, bundling, and leveraging mechanisms, while governance and integration conditions shape whether these mechanisms produce disciplined cross-functional action.

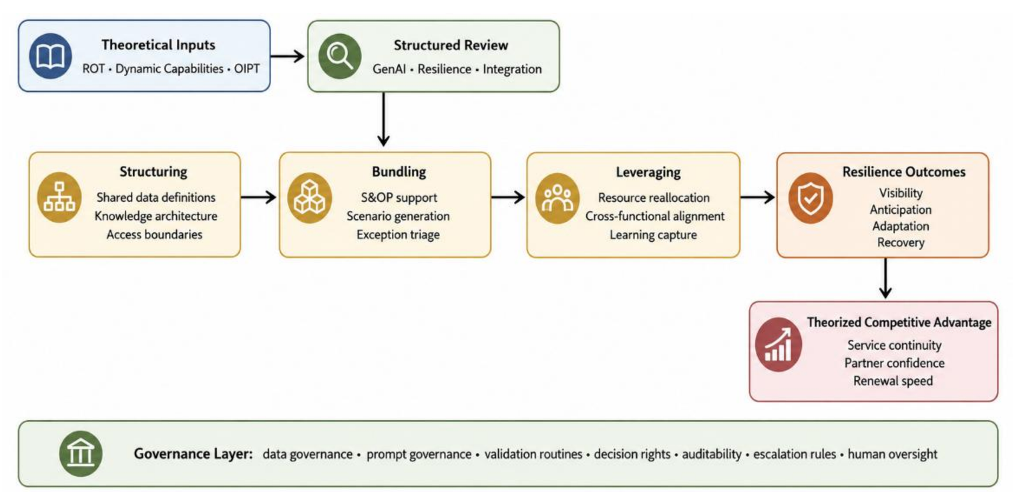


Figure 1. Conceptual framework of GenAI-enabled cognitive orchestration.

4.1 Structuring Cross-Functional Intelligence Resources

The first stage of cognitive orchestration is the structuring of cross-functional intelligence resources. Under disruption, relevant knowledge is distributed across supplier updates, demand signals, production constraints, transport status, customer commitments, inventory exposure, financial risk, and external threat information. Many firms already possess these resources, but they often remain fragmented across systems, teams, and decision levels. From a Resource Orchestration Theory perspective, value creation begins when managers define what information is relevant, who can access it, how terms are standardized, and how digital knowledge repositories are connected to human expertise. GenAI may support this structuring process by transforming unstructured text into searchable summaries, translating technical information into decision-ready narratives, and aligning terminology across procurement, planning, logistics, finance, and customer-facing functions. However, this benefit depends on shared data definitions, approved source boundaries, common disruption categories, prompt governance, and clear escalation rules. If different functions rely on inconsistent master data, conflicting assumptions, or ungoverned prompts, GenAI may produce competing interpretations rather than shared situational awareness. Therefore, the effect of GenAI on resilience depends first on whether firms create a coherent cross-functional intelligence architecture.

P1. The positive relationship between GenAI use and supply chain resilience is strengthened when firms structure cross-functional intelligence resources through shared data definitions, approved information boundaries, and common disruption taxonomies.

4.2 Bundling GenAI into Recurring Cross-Functional Decision Routines

The second stage is bundling. Structuring intelligence resources is insufficient unless those resources are embedded into repeatable decision routines. In supply chains, such routines include sales and operations planning, supplier-risk reviews, logistics exception triage, inventory allocation meetings, crisis-response calls, customer-priority decisions, and post-disruption learning reviews. GenAI may improve these routines by summarizing supplier communications, generating comparable response scenarios, retrieving precedent cases, drafting role-specific briefings, and clarifying trade-offs among service, cost, capacity, and cash. The theoretical point is not that GenAI replaces managerial judgment. Rather, GenAI may improve the quality and speed of collective judgment when its outputs are embedded in governed routines. A GenAI assistant used informally by one function may increase local productivity, but it does not necessarily improve resilience. Cognitive orchestration emerges when GenAI-supported outputs become part of recurring cross-functional decision processes in which assumptions are transparent, outputs are validated, and trade-offs are reconciled across functions.

P2. Embedding GenAI in recurring cross-functional decision routines positively influences supply chain resilience by improving information sharing, option generation, and alignment speed.

The effect of these routines is likely to depend on internal integration. If functions continue to use isolated metrics, incompatible assumptions, or separate decision criteria, GenAI-generated outputs may be interpreted differently across the organization. In contrast, when internal integration is strong, GenAI-supported summaries and scenarios can create a more consistent basis for collective action.

P3. The positive effect proposed in P2 is stronger when internal integration is high and weaker when functions retain isolated metrics, prompt logics, and decision criteria.

4.3 Leveraging Cognitive Orchestration for Resilience Outcomes

The third stage is leveraging. Once GenAI is embedded in cross-functional routines, managers must mobilize those routines for adaptive action. Cognitive orchestration may strengthen resilience through five linked outcomes: visibility, anticipation, adaptive response, recovery, and learning. Visibility improves when fragmented updates are synthesized into shared situational awareness. Anticipation improves when teams examine possible second-order disruption effects. Adaptive response improves when alternative sourcing, routing, production, inventory, and customer-allocation options can be compared more quickly. Recovery improves when response activities are coordinated and documented. Learning improves when disruption experience is converted into reusable playbooks and updated routines. These mechanisms align with dynamic capability logic. GenAI may support sensing by synthesizing weak signals, seizing by preparing response alternatives, and reconfiguring by helping managers compare and document resource redeployment options. However, GenAI-supported interpretation does not create resilience unless managers can translate insights into action. The link between cognition and resilience therefore depends on managerial reconfiguration capability: the authority, willingness, and organizational capacity to redeploy resources and adjust workflows under uncertainty.

P4. GenAI-enabled cognitive orchestration positively influences supply chain resilience through improvements in visibility, anticipation, adaptive response, recovery, and organizational learning.

P5. The relationship proposed in P4 is mediated by managerial reconfiguration capability, because GenAI-supported interpretation improves resilience only when decision makers can translate insights into resource redeployment and workflow adjustment.

4.4 Converting Resilience into Competitive Advantage

Resilience becomes strategically meaningful when it produces value beyond operational recovery. Firms that maintain service continuity, communicate credibly, recover faster, and learn more effectively from disruption may strengthen customer trust, partner confidence, and strategic renewal. In this sense, resilience may contribute to competitive advantage when it differentiates the firm's reliability and responsiveness relative to competitors. This relationship should be treated cautiously. Because the paper is conceptual, competitive advantage is theorized as a downstream possibility rather than demonstrated as an empirical outcome. GenAI-enabled cognitive orchestration may support competitive advantage only when resilience gains are consistent, governed, and visible to customers, suppliers, and internal decision makers. Poorly governed GenAI use may damage credibility by producing incorrect promises, inconsistent explanations, or unsupported response decisions. Thus, competitive advantage is not an automatic result of GenAI adoption; it is a contingent outcome of disciplined cognitive orchestration.

P6. Firms that leverage GenAI for cross-functional cognitive orchestration are more likely to convert resilience capabilities into competitive advantage through stronger service continuity, response credibility, relationship quality, and renewal speed, provided that governance quality and cross-functional integration remain high.

4.5 Governance, Risks, and Implementation Contingencies

Governance is central to the framework because GenAI can introduce new risks into disruption response. It may generate hallucinated summaries, expose confidential data, reinforce biased assumptions, encourage overreliance, produce conflicting outputs across functions, or weaken accountability if decision rationales are not traceable. These risks are especially serious in supply chains because AI-supported decisions may affect customer commitments, supplier relationships, transport priorities, regulatory exposure, and financial allocation. Figure 2 illustrates the governance architecture required for cognitive orchestration. The governance logic begins with input controls, including approved data sources, access rules, and confidentiality boundaries. It then requires interaction controls such as prompt templates, versioning, and role-specific use guidelines. Decision controls are needed to define validation checkpoints, escalation thresholds, and final decision authority. Monitoring controls support traceability, audit logs, and performance review. Learning controls ensure that disruption experience is converted into improved routines rather than lost after the event.

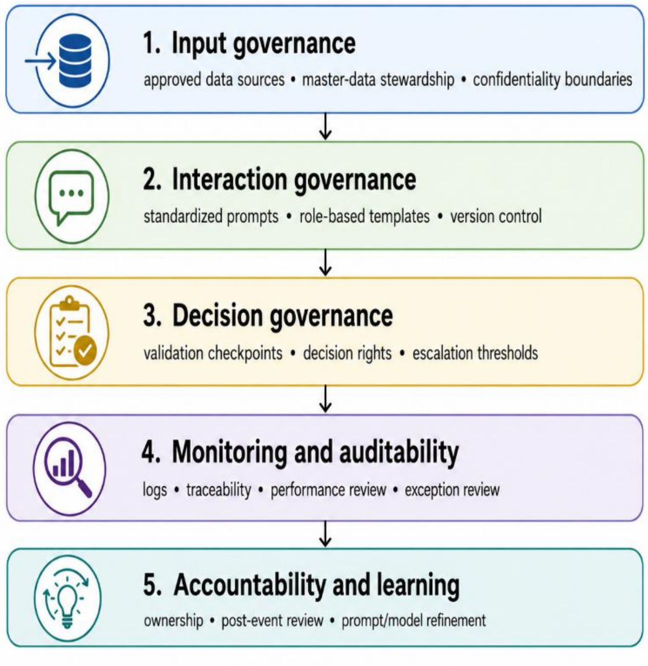


Figure 2. Governance architecture for GenAI-enabled cognitive orchestration

These governance mechanisms are not administrative details; they determine whether GenAI outputs become credible inputs to coordinated decision-making. When governance quality is high, GenAI may reduce information-processing bottlenecks and improve response discipline. When governance is weak, the same technology may increase noise, false confidence, interpretive conflict, and coordination risk.

P7. The positive effects of GenAI-enabled cognitive orchestration on resilience are contingent on governance quality, data integrity, cross-functional trust, and decision-right clarity; absent these conditions, GenAI may amplify coordination risk, false confidence, and interpretive conflict rather than strengthen resilience. As table 4 summarizes the proposition logic and identifies future empirical testing pathways. The table clarifies the theoretical relationship, core mechanism, expected outcome, and possible testing approach for each proposition. Whereas table 5 summarizes the main governance risks and control mechanisms associated with GenAI-enabled cognitive orchestration. The purpose of the table is to show that governance is not separate from resilience; it is one of the conditions that determines whether GenAI-supported coordination becomes reliable.

Table 4. Proposition logic and future empirical testing pathways

Proposition	Theoretical relationship	Core mechanism	Theorized outcome	Future testing approach
P1	Enabling condition	Shared data definitions and approved information boundaries improve structured intelligence use	Higher visibility and common situational awareness	Survey measures of data standardization, information quality, and resilience visibility
P2	Antecedent effect	Embedding GenAI in recurring routines improves information sharing, option generation, and alignment speed	Better response readiness and coordination speed	Comparative case studies of S&OP, crisis-response, or supplier-risk routines with and without GenAI support
P3	Moderation effect	Internal integration conditions whether GenAI outputs are interpreted consistently across functions	Stronger or weaker benefits from GenAI-enabled routines	Moderated regression or PLS-SEM using internal integration as moderator
P4	Direct conceptual relationship	Cognitive orchestration enhances visibility, anticipation, adaptive response, recovery, and learning	Higher supply chain resilience capability	Survey-based measurement of cognitive orchestration and resilience capability
P5	Mediated relationship	Managerial reconfiguration capability translates GenAI-supported interpretation into action	More effective resource redeployment and recovery	Mediation model using reconfiguration capability as mediator
P6	Conditional downstream effect	Resilience gains support service continuity, credibility, relationship quality, and renewal	Theorized competitive advantage	Longitudinal designs linking resilience metrics to customer, supplier, and performance outcomes
P7	Moderation or contingency effect	Governance quality shapes whether GenAI outputs are trusted, validated, and usable	Lower false confidence and more disciplined adoption	Comparative case studies or survey models across governance maturity levels

Table 5. Governance risks and control mechanisms

Risk or failure mode	Why it matters in supply chains	Primary control	Resilience consequence if unmanaged
Hallucinated synthesis	May misstate supplier status, inventory exposure, transport disruption, or response options	Human validation against source records before action	Incorrect response decisions and reduced recovery quality
Data leakage	May expose confidential supplier, customer, pricing, or contractual information	Role-based access control and approved data boundaries	Loss of partner trust and increased compliance risk
Bias or skewed prioritization	May disadvantage certain suppliers, customers, routes, or product categories	Periodic review, exception testing, and diverse reviewer input	Unfair or strategically damaging allocation decisions
Overreliance	Teams may accept outputs without challenge during high-pressure disruption events	Mandatory human sign-off for materially consequential decisions	False confidence and weak managerial judgment
Poor traceability	Difficult to reconstruct why a decision was made after disruption	Audit logs, prompt versioning, and retained decision records	Weak accountability and poor post-disruption learning
Conflicting outputs across functions	Creates interpretive conflict and slows coordinated response	Standardized prompt libraries, common taxonomies, and escalation rules	Slower alignment and fragmented response
Unclear escalation	Critical issues may circulate without timely decision ownership	Threshold-based escalation rules and decision-right matrices	Delayed reconfiguration and avoidable service failure

5. Discussion

This paper develops GenAI-enabled cognitive orchestration as a conceptual explanation for how generative AI may support supply chain resilience through cross-functional decision-making. The framework does not argue that GenAI automatically improves resilience. Rather, it argues that GenAI becomes strategically relevant when it is governed, embedded in recurring decision routines, connected to cross-functional interpretation, and linked to managerial reconfiguration authority. This distinction matters because AI research in supply chain risk and resilience increasingly shows that digital intelligence is valuable only when it supports decision processes, risk interpretation, and adaptive response rather than isolated technical performance (Baryannis et al., 2019; Belhadi et al., 2022; Modgil et al., 2022).

5.1 Theoretical Implications

The framework contributes to the supply chain resilience and AI literature by shifting attention from AI adoption to AI-enabled orchestration. Prior research has shown that AI and big data analytics may support supply chain resilience by improving risk detection, readiness, response, recovery, and adaptability (Zamani et al., 2022). However, the present framework argues that these effects require an additional organizational explanation: firms must convert AI-supported information into cross-functional routines and reconfiguration actions. This helps explain why similar digital tools may produce different resilience outcomes across firms.

The framework also extends work on analytics capability and supply chain resilience by emphasizing the role of cross-functional interpretation. Data analytics capability may strengthen information-processing capacity and complement organizational flexibility during disruption (Dubey et al., 2021). GenAI-enabled cognitive orchestration builds on this logic but adds a more specific mechanism: the translation of dispersed knowledge into shared narratives, validated scenarios, and decision-ready response options. In this sense, GenAI is not merely another analytics layer; it may operate as a coordination medium when it is governed and embedded in routines. The framework further contributes to AI-enabled supply chain resilience research by treating resilience as a socio-technical outcome. AI-based decision frameworks can support resilience strategy development, but their value depends on the organizational capacity to interpret, validate, and act on AI-supported outputs (Belhadi et al., 2022). Cognitive orchestration therefore clarifies the missing organizational layer between AI capability and resilience outcomes. It specifies that structuring intelligence resources, bundling routines, and leveraging reconfiguration authority are necessary mechanisms through which GenAI may become strategically useful.

5.2 Boundary Conditions and Failure Mechanisms

The framework also identifies clear boundary conditions. GenAI-enabled cognitive orchestration is less likely to strengthen resilience where master data are unreliable, functions are politically fragmented, digital infrastructure is immature, or decision rights are ambiguous. Digital supply chain surveillance research shows that AI can improve visibility and risk detection, but it also raises concerns around data quality, surveillance scope, interpretability, and governance (Brintrup et al., 2024). These concerns become more serious when GenAI is used in cross-functional disruption response because outputs may influence supplier commitments, customer communication, inventory allocation, transport priorities, and financial exposure. Several failure mechanisms are especially important. First, hallucinated or poorly grounded synthesis may distort supplier status, transport exposure, inventory availability, or customer commitments. Second, inconsistent prompts and data definitions may generate conflicting interpretations across functions. Third, overreliance may weaken managerial judgment when teams accept AI-supported recommendations without source verification. Fourth, poor traceability may prevent firms from learning why a disruption response succeeded or failed. Fifth, weak governance may expose confidential supplier, customer, pricing, or contractual information. These risks are consistent with human-centered AI research, which emphasizes that safe and trustworthy AI requires both automation capability and meaningful human control (Shneiderman, 2020). The need for human validation is not simply a compliance issue; it is central to decision quality. Human-AI interaction research shows that AI systems should support user understanding, enable effective intervention, and make system behavior observable enough for appropriate reliance (Amershi et al., 2019). Similarly, AI risk-management guidance emphasizes validity, reliability, safety, security, accountability, transparency, explainability, privacy, and fairness as core elements of trustworthy AI systems (NIST, 2023). These principles directly support the governance architecture proposed in this paper. Without validation checkpoints, access controls, audit trails, escalation rules, and accountability ownership, GenAI may increase speed while reducing resilience discipline.

5.3 Managerial Implications

For managers, the framework suggests that GenAI adoption should begin with decision architecture rather than generic chatbot deployment. Firms should identify the disruption-related routines where cross-functional coordination is slow, inconsistent, or information-intensive. Practical entry points include supplier-risk reviews, sales and operations planning, logistics exception triage, inventory allocation, customer-priority decisions, and post-disruption learning reviews. Research on AI for supply chain resilience similarly emphasizes that AI value emerges through visibility, risk recognition, decision support, and response capability rather than technology use alone (Modgil et al., 2022). Managers should also distinguish between AI outputs and decision authority. A GenAI-generated scenario should not be treated as a decision; it should be treated as an input to validated managerial judgment. This distinction is important because digital supply chain monitoring can expand the amount of visible information while still requiring interpretation, prioritization, and governance before action (Brintrup et al., 2024). The managerial task is therefore to define who validates GenAI outputs, who owns the decision, what evidence is required before action, and what escalation threshold applies during disruption. Managers should measure GenAI-enabled orchestration using resilience-oriented indicators rather than simple adoption metrics. Prompt volume, user counts, or chatbot activity do not show whether resilience has improved. More relevant indicators include detection latency, alignment speed, scenario quality, exception closure time, recovery cycle time, service continuity, decision traceability, and lesson reuse. These metrics are consistent with the broader shift in AI and analytics research from technological adoption toward organizational capability, decision quality, and resilience performance (Dubey et al., 2021; Zamani et al., 2022).

Table 6 translates the framework into illustrative GenAI use cases across supply chain functions. The table is not intended as empirical evidence; rather, it shows how cognitive orchestration may be operationalized in practical decision routines.

Table 6. Illustrative GenAI use cases across supply chain functions

Function	Illustrative GenAI use case	Potential resilience benefit	Governance requirement
Procurement	Summarize supplier communications and prepare supplier-risk briefs	Earlier signal detection and faster supplier-response coordination	Source-grounded summaries and supplier-data access controls
Planning / S&OP	Generate scenario packs linking demand, supply, capacity, and inventory trade-offs	Faster cross-functional alignment during volatility	Validated assumptions and standardized scenario templates
Manufacturing	Translate operational disruptions into management-level response options	Quicker escalation and clearer downstream impact assessment	Verification against shop-floor and production-control data
Logistics	Triage transport exceptions and compare rerouting alternatives	Reduced response latency and improved delivery continuity	Carrier-data validation and escalation thresholds

Customer service / commercial	Draft customer-facing disruption updates and allocation rationales	More credible communication with customers and partners	Human review before external communication
Finance / risk	Synthesize cost, cash, exposure, and service implications during disruption	Better prioritization of trade-offs across cost and continuity	Role-based access to sensitive financial information
Post-disruption learning	Generate structured after-action reviews and reusable playbooks	Faster organizational learning and routine refinement	Audit trails, ownership, and post-event validation

5.4 Future Empirical Testing

The framework now requires empirical validation. Survey research could test whether GenAI-enabled cognitive orchestration is associated with resilience outcomes such as visibility, anticipation, adaptive response, recovery, and learning. Multi-respondent designs would be preferable because cognitive orchestration is cross-functional and cannot be reliably measured from a single managerial perspective. Procurement, planning, logistics, operations, finance, and customer-facing respondents may perceive orchestration quality differently. Case-study research could examine how firms embed GenAI into actual disruption-response routines. Comparative case studies would be especially valuable because they could explain why similar GenAI tools produce different outcomes across firms. For example, researchers could compare organizations with strong and weak governance maturity, or firms with high and low internal integration. Such studies would extend AI-enabled resilience research by showing whether AI-supported decision frameworks work differently across governance and integration conditions (Belhadi et al., 2022; Modgil et al., 2022). Longitudinal research is also needed. Resilience is not fully visible in a single decision episode; it develops through repeated disruption, recovery, and learning cycles. Longitudinal designs could examine whether GenAI-supported routines reduce detection latency, improve recovery cycle time, increase lesson reuse, or strengthen service continuity over time. Existing reviews of AI and big data analytics in resilience show that AI may support readiness, response, recovery, and adaptability, but future research needs stronger process-level evidence explaining how those effects unfold inside organizations (Zamani et al., 2022). Future research should also test the proposed boundary conditions. Governance quality, data integrity, internal integration, trust, and decision-right clarity should be examined as moderators. Managerial reconfiguration capability should be examined as a mediator between cognitive orchestration and resilience outcomes. Competitive advantage should be tested cautiously through downstream indicators such as customer retention, partner confidence, service reliability, recovery speed, and renewal capability. Research on human-AI interaction and trustworthy AI suggests that such models should include not only performance outcomes, but also validation quality, appropriate reliance, transparency, auditability, and accountability (Amershi et al., 2019; Shneiderman, 2020; NIST, 2023).

6. Conclusion

This paper developed a conceptual framework explaining how generative artificial intelligence may function as a cognitive orchestration capability for supply chain resilience. Integrating Resource Orchestration Theory, Dynamic Capabilities, and Organizational Information Processing Theory, the paper argues that GenAI becomes strategically relevant not through isolated automation, but through its governed embedding in cross-functional decision routines. The central claim is that GenAI may support resilience when firms use it to structure distributed intelligence resources, bundle them into recurring decision processes, and leverage them for adaptive response, recovery, and organizational learning. The framework advances the concept of cognitive orchestration to clarify how GenAI may connect fragmented knowledge, shared interpretation, and coordinated action across supply chain functions. This contribution is important because disruptions rarely affect procurement, production, logistics, finance, sales, or customer service in isolation. Resilience therefore depends on more than local analytical accuracy; it depends on whether organizations can translate distributed signals into validated scenarios, timely decisions, and resource reconfiguration under uncertainty. The paper also emphasizes that GenAI-enabled resilience is conditional. Data integrity, human oversight, prompt governance, auditability, cross-functional trust, and decision-right clarity determine whether GenAI outputs become credible inputs to coordinated action. Without these conditions, GenAI may increase false confidence, interpretive conflict, overreliance, and accountability risk. The framework therefore positions governance not as an implementation add-on, but as a constitutive element of cognitive orchestration. Because the study is conceptual, the propositions should be interpreted as future research pathways rather than confirmed causal relationships. Empirical studies are needed to test whether GenAI-enabled cognitive orchestration improves measurable resilience outcomes such as detection latency, alignment speed, response quality, recovery cycle time, service continuity, and post-disruption learning. Future work should also examine whether resilience gains translate into competitive advantage through stronger partner confidence, service reliability, and organizational renewal. The core implication is clear: the promise of GenAI in supply chains lies not in content generation alone, but in the disciplined orchestration of distributed knowledge into governed cross-functional action.

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