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AI-Driven Supply Chain Resilience in the U.S. Hospitality Sector

Authors:

Salami Abdul Mohammed (s.mohammed.8712@westcliff.edu)
College of Business, Westcliff University, Irvine, California, USA

Abstract:

This study examines how Artificial Intelligence (AI) reshapes dynamic capabilities and enhances supply chain resilience within multi-tier hospitality supply networks in the United States. Anchored in Dynamic Capabilities Theory (DCT) and employing a qualitative multi-tier design, ten supply chain professionals across a luxury hotel, regional distributors, and a national supplier were interviewed. Data were analyzed abductively to examine how AI influences sensing, seizing, and transforming capabilities across interacting supply tiers. Findings reveal that AI disproportionately strengthens sensing through algorithmic forecasting and real-time analytics, while seizing capabilities develop moderately and transforming remains incremental. Capability development is uneven across supply tiers, with upstream distributors exhibiting stronger AI-enabled sensing than hotel actors. The study extends DCT into service-intensive hospitality supply ecosystems by reconceptualizing sensing as algorithmically embedded and introducing the concept of distributed capability asymmetry, demonstrating how uneven AI maturity across supply tiers shapes network-level resilience outcomes.

Keywords:

Artificial Intelligence, Supply Chain Resilience, Dynamic Capabilities, Hospitality, Digital Transformation

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Introduction

The U.S. hospitality sector operates within an increasingly volatile supply environment characterized by demand unpredictability, perishability constraints, climate-related disruptions, geopolitical instability, and global health crises. The COVID-19 pandemic, in particular, exposed structural fragilities in global and domestic supply networks, disrupting procurement routines, logistics coordination, and inventory systems across service industries (Ivanov & Dolgui, 2020; Queiroz et al., 2020). Unlike manufacturing supply chains, hospitality operations depend on time-sensitive inputs, fluctuating customer demand, and real-time coordination across multiple upstream actors, heightening exposure to disruption and amplifying the strategic importance of supply chain resilience in service ecosystems.

The hospitality industry is economically significant yet structurally vulnerable. In the United States alone, the hotel industry contributes over one trillion dollars to economic activity and supports millions of jobs (American Hotel & Lodging Association [AHLA], 2023). Perishability of food and beverage inputs, service-level commitments, and global sourcing dependencies intensify susceptibility to disruption. These features make hospitality a particularly revealing empirical context for examining how resilience is constructed under sustained environmental turbulence.

Supply chain resilience is commonly defined as the capability to anticipate, respond to, and recover from disruptions while maintaining operational continuity (Ponomarov & Holcomb, 2009). Traditional resilience strategies in hospitality emphasize redundancy mechanisms, including supplier diversification, safety stock, and relational coordination (Sheffi & Rice, 2005). While buffering mechanisms enhance recovery capacity, they are inherently reactive and may be insufficient in digitally interconnected environments characterized by persistent uncertainty. Increasingly, resilience depends not only on redundancy but also on adaptive capacity, the ability to detect environmental shifts, mobilize resources, and reconfigure operations in response to turbulence.

Dynamic Capabilities Theory (DCT) provides a foundational lens for examining such adaptive processes. Teece (2007) conceptualizes dynamic capabilities as comprising three higher-order activities: sensing opportunities and threats, seizing opportunities through resource orchestration, and transforming organizational structures to sustain competitiveness. Although DCT has been widely applied in manufacturing and technology-intensive contexts, its application in service-intensive hospitality supply ecosystems remains limited. Moreover, existing research often assumes that dynamic capabilities are primarily firm-level phenomena and that sensing, seizing, and transforming evolve in relatively integrated and symmetrical ways.

The rise of Industry 4.0 technologies has introduced new mechanisms for enhancing adaptive capacity. Artificial Intelligence (AI), predictive analytics, and digital platforms increasingly enable data-driven

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decision-making in supply chain management (Kamble et al., 2018). AI applications in supply chains include demand forecasting, anomaly detection, route optimization, and inventory management (Min, 2010; Belhadi et al., 2021). From a dynamic capabilities perspective, AI may strengthen sensing by embedding predictive intelligence into operational systems, enhance seizing through improved coordination and resource allocation, and potentially support transforming via automation and digital reconfiguration.

Despite growing attention to AI-enabled supply chain resilience, empirical research remains concentrated in manufacturing sectors or treats digitalization primarily as a performance-enhancing tool (Ivanov, 2021; Belhadi et al., 2021). Limited attention has been devoted to understanding how AI reshapes adaptive processes within hospitality supply networks. Furthermore, little is known about how sensing, seizing, and transforming capabilities are distributed across buyer and supplier nodes within multi-tier service ecosystems.

This study addresses these gaps by examining how AI-enabled technologies contribute to supply chain resilience within the U.S. hospitality sector. Drawing on qualitative data from procurement actors within a luxury hotel and upstream distributors and suppliers, the study adopts a multi-tier network perspective to capture cross-organizational capability enactment. The study advances scholarship in three ways: first, it extends DCT into a service-intensive hospitality supply context characterized by volatility and perishability; second, it reconceptualizes sensing as increasingly algorithmically mediated rather than solely managerial; and third, it introduces the concept of distributed capability asymmetry. Accordingly, the study addresses the following research questions:

RQ1: How does AI reshape sensing, seizing, and transforming capabilities within hospitality supply networks?

RQ2: How are these AI-enabled dynamic capabilities distributed across supply chain tiers?

RQ3: How does cross-tier variation in AI maturity influence supply chain resilience?

Literature Review

Dynamic Capabilities and Supply Chain Resilience

Supply chain resilience is commonly defined as the capability of a supply network to prepare for, respond to, and recover from disruptions while maintaining operational continuity (Ponomarov & Holcomb, 2009). Early research emphasized structural design mechanisms such as redundancy, flexibility, and agility as buffers against supply shocks (Sheffi & Rice, 2005; Tang, 2006). In this tradition, resilience was primarily conceptualized as robustness achieved through excess capacity and multiple sourcing.

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More recent scholarship reframes resilience as an adaptive, dynamic capability requiring reconfiguration under systemic uncertainty. Ivanov and Dolgui (2020) extend resilience toward survivability in intertwined supply networks, while Wieland and Durach (2021) argue that resilience must be understood as an ongoing capability of alignment and renewal rather than static buffering. Post-pandemic research further emphasizes viability and adaptability under persistent turbulence (Ivanov, 2021; Chowdhury et al., 2023).

Dynamic Capabilities Theory (DCT) offers a central explanatory lens for this adaptive logic. Teece (2007, 2014) conceptualizes dynamic capabilities as comprising sensing, seizing, and transforming. Contemporary debates increasingly question whether these capabilities remain firm-bound in digitally mediated environments. Helfat and Raubitschek (2018) argue that digital ecosystems redistribute innovation and orchestration beyond traditional firm boundaries. More recent work suggests that digital infrastructures may partially externalize sensing and coordination processes (Nambisan et al., 2022). Despite this shift, empirical applications of DCT in supply chain contexts remain largely manufacturing-focused and firm-centric. The implications of distributed digital infrastructures for capability location and asymmetry in service-intensive hospitality ecosystems remain insufficiently theorized.

AI-Enabled Resilience in Supply Chains

AI, big data analytics, and Industry 4.0 technologies have been widely examined as enablers of supply chain resilience in manufacturing systems. AI-driven predictive analytics enhances demand forecasting, inventory optimization, and disruption detection (Belhadi et al., 2021; Ivanov, 2021). Mandal (2019) demonstrates that analytics capability strengthens preparedness and agility, while Ivanov and Dolgui (2020) highlight the role of digital simulation and reconfiguration under crisis conditions.

Recent 2022–2024 research deepens this conversation. Chowdhury et al. (2023) show that digital supply chain technologies enhance resilience through improved visibility and information sharing, yet emphasize uneven capability development across networks. Dubey et al. (2023) find that AI-enabled analytics capability interacts with organizational culture and governance to influence resilience outcomes, suggesting that technological deployment alone is insufficient. Similarly, Bode and Macdonald (2023) argue that digitalization may amplify resilience but can also create new dependencies and vulnerabilities across inter-firm networks.

However, most AI-resilience studies assume structured production systems and relatively standardized flows. They often evaluate resilience through operational performance metrics rather than examining distributed capability dynamics. The question of how algorithmic sensing intensity varies across supply tiers, and how that asymmetry shapes resilience, remains underdeveloped.

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Digitalization and Ecosystem Capability

Digital transformation research increasingly emphasizes ecosystems, platforms, and infrastructural interdependence. Nambisan et al. (2022) argue that digital technologies reshape innovation processes by embedding capabilities within shared infrastructures rather than individual firms. Kapoor (2023) further shows that ecosystem structures influence competitive advantage through complementarities and capability distribution.

Recent strategic management work highlights that dynamic capabilities in digital ecosystems may be relational rather than internalized. Adner (2017) introduced the concept of ecosystem-as-structure, and subsequent research has elaborated how capability orchestration and complementarity shape performance across interconnected actors. More recently, Helfat and Peteraf (2023) discuss how digital contexts challenge traditional microfoundations by redistributing sensing and coordination through algorithmic systems. Yet, while ecosystem literature recognizes interdependence, it rarely theorizes the stratification of algorithmic capability intensity across tiers within supply networks.

Artificial Intelligence as a Dynamic Capability Enabler

Artificial Intelligence refers to computational systems capable of learning from data, recognizing patterns, and supporting decision-making (Min, 2010; Huang & Rust, 2018). In supply chains, AI applications include predictive forecasting, anomaly detection, and route optimization (Belhadi et al., 2021). From a dynamic capabilities perspective, AI may enhance sensing by embedding predictive intelligence into operational routines. Warner and Wäger (2019) conceptualize digital dynamic capabilities as the ability to master digital transformation. Recent work extends this by arguing that digital infrastructures may partially relocate sensing processes from managerial cognition to algorithmic systems (Nambisan et al., 2022).

AI may also enhance seizing through optimized resource orchestration, while transforming may involve automation and digital integration. However, recent evidence suggests transformation is often path-dependent and institutionally constrained (Dubey et al., 2023; Chowdhury et al., 2023). In hospitality contexts, digitalization research largely focuses on customer-facing technologies such as service robots and AI-enabled personalization (Huang & Rust, 2018; Ivanov & Webster, 2019). Upstream supply chain processes remain underexamined. Moreover, the intersection of AI, distributed dynamic capabilities, and multi-tier service ecosystems has not been systematically theorized. This study addresses that gap by examining how algorithmic sensing, resource orchestration, and socio-technical reconfiguration operate across hospitality supply tiers.

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Methods and Data

Research Design

This study adopts a qualitative, abductive research design to examine how AI-enabled dynamic capabilities are enacted and distributed across a multi-tier hospitality supply ecosystem under conditions of environmental volatility. Given the limited theorization of digitally mediated dynamic capabilities in service-intensive supply networks, qualitative inquiry is particularly appropriate for uncovering relational, processual, and socio-technical mechanisms that remain underexplored in existing research (Eisenhardt, 1989; Gioia et al., 2013).

Rather than testing predefined hypotheses, the study engages in theory elaboration by refining the microfoundations and boundary conditions of DCT within a digitally evolving service context (Lee et al., 1999). An abductive logic guided the research process, enabling iterative movement between empirical observations and established theoretical constructs (Dubois & Gadde, 2002). This approach is especially suitable when theory requires re-specification rather than straightforward application.

Unit of Analysis and Boundary Conditions

The unit of analysis is a multi-tier hospitality supply network anchored around a focal luxury hotel and its upstream distributors and suppliers. This network-level orientation reflects the interdependent nature of supply chain resilience, which emerges through coordinated action across interacting actors rather than within isolated organizational boundaries (Ponomarov & Holcomb, 2009; Ivanov & Dolgui, 2020). Boundary conditions were defined along four dimensions: (1) the U.S. hospitality sector as empirical context; (2) supply chains exposed to systemic volatility including demand fluctuations and post-pandemic turbulence; (3) procurement and distribution professionals directly involved in operational coordination; and (4) AI-enabled systems related to forecasting, logistics, and inventory management. The objective is analytical generalization through theoretical refinement rather than statistical inference (Yin, 2018).

Sampling Strategy and Participant Profile

Participants were selected using purposive, network-based sampling to ensure theoretical relevance to AI-enabled adaptive processes (Patton, 2015). The final sample comprised ten supply chain professionals distributed across three interconnected tiers: hotel-side procurement actors (Tier 1), regional distributors and purveyors (Tier 2), and a national food distribution corporation (Tier 3). Participants occupied procurement, logistics, warehousing, and operational management roles and possessed between eight and more than twenty years of supply chain experience.

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While the sample of ten participants may appear modest, the multi-tier design and the iterative nature of data collection ensured analytical depth. Sampling continued until theoretical saturation was achieved at the level of dynamic capability configurations rather than descriptive code repetition (Guest et al., 2006). After the eighth participant, no substantively new sensing–seizing–transforming patterns emerged, and subsequent interviews reinforced existing interpretive structures.

Data Collection

Data were collected over a three-month period between October and December 2025. Each participant engaged in multiple interview interactions, with a minimum of four engagements per participant. This iterative design enabled clarification of responses, follow-up probing, and refinement of emerging interpretations, thereby strengthening analytical depth. Prior to the main study, pilot interviews were conducted to refine the interview protocol; pilot data were excluded from the final dataset.

Semi-structured interviews lasting approximately 30–35 minutes were conducted face-to-face. The interview protocol explored participants' experiences with supply chain disruptions, resilience mechanisms, and coordination practices; AI awareness and implementation stages; perceived benefits and risks of AI adoption; and organizational readiness for digital transformation. All interviews were audio-recorded and transcribed verbatim. Ethical clearance was obtained from the institutional review board prior to data collection, and identifiers were removed during transcription.

Data Analysis

Data analysis followed a structured, multi-stage process consistent with qualitative theory-building methodologies (Eisenhardt, 1989; Gioia et al., 2013). In the first stage, open coding was conducted to generate inductive first-order concepts grounded in participants' language. In the second stage, codes were clustered into higher-order categories reflecting structural redundancy mechanisms, AI-enabled adaptive processes, and socio-technical transformation dynamics. Only after empirical categories stabilized were patterns abductively aligned with the sensing–seizing–transforming dimensions of DCT (Teece, 2007). The coding process progressed from 52 first-order in vivo codes to 14 second-order categories, subsequently aggregated into six higher-level theoretical dimensions. A coding tree is presented in Appendix A.

Treatment of AI Maturity Variation and Methodological Rigor

Participants represented heterogeneous stages of AI adoption, ranging from exploratory awareness and pilot experimentation to fully embedded predictive systems. The analysis distinguished between AI as discourse, AI as experimentation, and AI as embedded operational system—preventing conflation of rhetorical commitment with enacted transformation. Methodological rigor was ensured through cross-

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tier triangulation, iterative member clarification, systematic comparison, detailed audit trails, peer debriefing, and reflexive memo-writing, consistent with Lincoln and Guba's (1985) criteria of credibility, dependability, confirmability, and transferability.

Results

RQ1: How Does AI Reshape Sensing, Seizing, and Transforming Capabilities?

Research question 1 is addressed through Themes 2, 4, and 6, which collectively trace the reconfiguration of dynamic capabilities from pre-digital managerial monitoring to algorithmically mediated adaptation.

Theme 2 (Structural Exposure to Environmental Volatility) establishes the pre-AI baseline of sensing. Participants describe turbulence as persistent, systemic, and multi-dimensional, yet detection mechanisms rely primarily on managerial vigilance, supplier communication, and experiential judgment. Sensing in this configuration is interpretive and reactive, consistent with Teece's (2007) cognition-centered microfoundations.

Theme 4 (AI as a Sensing Multiplier and Operational Accelerator) marks a qualitative shift. AI embeds predictive analytics into forecasting, routing, and inventory systems, converting sensing from episodic managerial scanning into continuous, data-driven detection. Seizing is correspondingly accelerated through optimized routing and dynamic resource allocation, though these adjustments largely refine existing coordination routines rather than replacing them.

Theme 6 (Socio-Technical Tensions in AI Integration) reveals the limits of transformation. Despite intensified sensing and optimized seizing, deep structural reconfiguration remains constrained by governance concerns, data privacy risks, and workforce implications. Transforming therefore appears incremental and institutionally bounded rather than radical. Taken together, AI reshapes dynamic capabilities asymmetrically, disproportionately amplifying sensing and moderately enhancing seizing while only weakly advancing transforming.

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Participant ID	Organization	Position / Role	Tier in Supply Network	Geographic Scope	Years in Supply Chain	Years in Hospitality
P1	Four Seasons Atlanta Hotel	Purchasing Manager	Hotel (Buyer)	Single Property (Atlanta)	22 years	10 years
P2	Four Seasons Atlanta Hotel	Procurement Staff	Hotel (Buyer)	Single Property (Atlanta)	15 years	15 years
P3	Four Seasons Atlanta Hotel	Procurement Role	Hotel (Buyer)	Single Property (Atlanta)	11 years	8 months
P4	Four Seasons Atlanta Hotel	Procurement Support	Hotel (Buyer)	Single Property (Atlanta)	8 years	6–8 months
P5	Edward Don & Company	Regional Sales Manager	Equipment Distributor (Tier 2)	Regional/Multi-State U.S.	11 years	11 years
P6	Gourmet Foods International	Senior Supply Chain Manager	Food Distributor (Tier 2)	Regional/Multi-State U.S.	20+ years	10 years
P7	FreshPoint Atlanta	Supply Chain Coordinator	Fresh Produce Distributor (Tier 2)	Regional (Southeast U.S.)	8 years	5 years

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Participant ID	Organization	Position / Role	Tier in Supply Network	Geographic Scope	Years in Supply Chain	Years in Hospitality
P8	Sysco Foods	Supply Chain Manager	National Distributor (Tier 3)	National (U.S.)	18+ years	12 years
P9	Farmers & Fishermen Purveyors	Procurement Manager	Seafood/Farm Purveyor (Tier 2)	Regional (Southeast U.S.)	10 years	7 years
P10	Halperns' Steak and Seafood	Operations Manager	Premium Meat & Seafood Distributor (Tier 2)	Regional/Multi-State U.S.	15+ years	10 years

Table 1: Demographic Profile of Interview Participants

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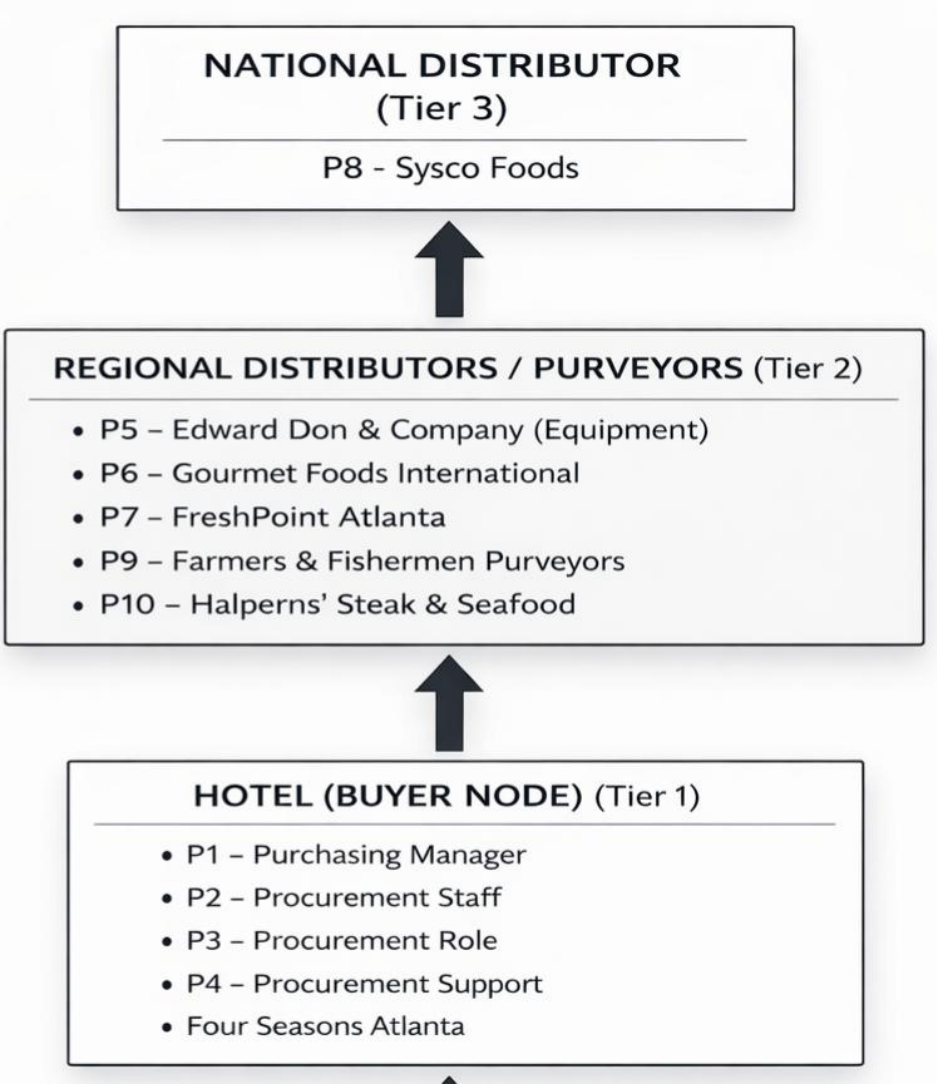


Figure 1: Multi-Tier Hospitality Network Participants Mapping. Source: Author's own illustration

Theme	**Core Dynamic Capability Dimension**	**Representative Codes**	**Illustrative Interview Excerpts**
Theme 2: Structural Exposure to Environmental Volatility	Baseline Sensing	Demand unpredictability; perishability risk; weather disruptions; pandemic exposure; supply uncertainty	*P1: "The unpredictability of supply chain disruptions... natural disasters... pandemics."*

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Theme	Core Dynamic Capability Dimension	Representative Codes	Illustrative Interview Excerpts
			P7: "Maintaining the freshness of perishable items during transit." *P8: "Managing changing customer demands... and dealing with bad weather occurrences."*
Theme 4: AI as a Sensing Multiplier and Operational Accelerator	Sensing → Seizing	Real-time analytics; predictive forecasting; anomaly detection; route optimization; automation of routine tasks	*P1: "Providing real-time data and predictive analytics."* *P6: "Implementing AI for demand forecasting and optimizing delivery routes."* *P10: "AI automation of routine tasks... reduces manual effort and human error."*
Theme 6: Socio-Technical Tensions in AI Integration	Transforming (Constrained)	Over-reliance on technology; data privacy; governance risks; workforce displacement; trust concerns	*P1: "Over-reliance on technology might reduce human oversight."* *P9: "Concerns about data privacy and security."* *P10: "Concern about job displacement."*

Table 2: RQ1 Analytical Mapping: Themes, Codes, and Interview Evidence

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RQ2: How Are AI-Enabled Dynamic Capabilities Distributed Across Supply Chain Tiers?

Research question 2 is addressed through cross-tier comparison of Themes 1, 4, and 5. Theme 1 (Operational Control as the Structural Backbone of Resilience) shows that all tiers possess established seizing routines grounded in procurement discipline, inventory continuity, and logistics coordination—ordinary capabilities that stabilize performance but do not inherently generate adaptation.

Clear asymmetries emerge in Theme 4. National distributors exhibit deeply embedded predictive analytics, integrated ERP systems, and real-time dashboards, enabling algorithmically intensified sensing and anticipatory adjustment. Regional distributors demonstrate partial digital orchestration, combining predictive tools with conventional coordination practices. Hotel-level actors, by contrast, display limited internal analytics capacity and rely heavily on supplier-generated forecasts. Sensing capability is therefore concentrated upstream rather than evenly distributed.

Theme 5 (Structural and Economic Conditions for AI Adoption) clarifies the mechanisms underpinning this asymmetry: infrastructure depth, capital investment, digital integration history, and skilled personnel availability condition AI embedding. The findings indicate that AI-enabled dynamic capabilities are relationally configured rather than firm-bound, supporting the concept of distributed capability asymmetry.

Theme	**Dynamic Capability Dimension**	**Cross-Tier Pattern**	**Illustrative Interview Evidence**
Theme 1: Operational Control as Structural Seizing Infrastructure	Seizing (Ordinary Capability Base)	All tiers maintain structured procurement, inventory and logistics routines	*P1 (Tier 1): "Oversee the procurement of all goods and services required for the hotel's operations."* *P8 (Tier 3): "Overseeing procurement, warehousing, and distribution."*
Theme 4: AI as a Sensing Multiplier	Sensing → Seizing	Tier 3: Advanced predictive analytics and integrated	*P8 (Tier 3): "We use predictive analytics models*

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Theme	Dynamic Capability Dimension	Cross-Tier Pattern	Illustrative Interview Evidence
and Operational Accelerator		systems Tier 2: Moderate forecasting and optimization Tier 1: Dependent on supplier-provided intelligence	*to forecast demand shifts across regions."* *P6 (Tier 2): "AI helps optimize delivery routes and anticipate fluctuations."* *P1 (Tier 1): "We depend on supplier-provided forecasts and updates."*
Theme 5: Structural and Economic Conditions for AI Adoption	Seizing (Capability Investment)	Infrastructure readiness and financial capacity determine AI maturity	*P3 (Tier 1): "Cost of implementation... return on investment... skilled personnel."* *P8 (Tier 3): "Organizational readiness and cost savings justify adoption."*
Cross-Tier Asymmetry (Derived Pattern)	Distributed Capability Configuration	Sensing intensity increases upstream; transforming remains limited across tiers	*P8 (Tier 3): "Our systems are fully integrated across logistics and forecasting."* *P1 (Tier 1): "Cost and infrastructure limit how far we can go with AI."*
Theme 6: Socio-Technical Tensions in AI Integration	Transforming (Constrained)	Incremental automation across tiers; limited structural redesign	*P10 (Tier 2): "Automation helps, but governance structures haven't changed dramatically."*

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Theme	Dynamic Capability Dimension	Cross-Tier Pattern	Illustrative Interview Evidence
			P1 (Tier 1): "We still rely heavily on human oversight."

Table 3: Cross-Tier Distribution of AI-Enabled Dynamic Capabilities

RQ3: How Does AI Maturity Shape Resilience Outcomes Across the Hospitality Supply Network?

At low levels of AI maturity, particularly within the hotel tier, resilience remains redundancy-based. Actors rely on multi-sourcing, buffer stock, and managerial oversight to absorb shocks. At moderate levels, selective digital integration enhances operational responsiveness through forecasting tools and route optimization. At high levels, most evident at the national distributor tier, sensing becomes predictive and anticipatory, enabling early anomaly detection and dynamic inventory reallocation.

Because AI maturity is unevenly distributed, resilience outcomes become stratified. Upstream actors detect turbulence earlier and mobilize responses more rapidly, while downstream hotel actors depend structurally on upstream intelligence flows. Resilience is therefore relational rather than autonomous. Importantly, increasing AI maturity does not generate proportional gains in transforming capabilities—governance reconfiguration and decision-right redistribution remain limited across all tiers, constrained by institutional caution and socio-organizational factors.

AI Maturity Level	Dominant Capability Pattern	Mechanism of Resilience	Cross-Tier Evidence	Theoretical Implication
Low (Hotel Tier)	Redundancy-based seizing	Reactive buffering through multi-sourcing and safety stock	*"We maintain multiple suppliers and buffer stock." (P3)*	Resilience remains structurally defensive

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AI Maturity Level	Dominant Capability Pattern	Mechanism of Resilience	Cross-Tier Evidence	Theoretical Implication
Moderate (Regional Tier)	Partial digital optimization	Accelerated response via selective forecasting and route adjustment	*"AI supports demand forecasting and delivery scheduling." (P6)*	Seizing enhanced but not fully algorithmic
High (National Tier)	Predictive sensing dominance	Anticipatory adjustment through real-time analytics and anomaly detection	*"We use predictive analytics for demand forecasting." (P8)*	AI maturity drives predictive preparedness
Across Tiers	Incremental transformation	Automation without governance redesign	*"AI reduces manual errors, but structure hasn't fundamentally changed." (P10)*	Transformation remains staged and institutionally constrained

Table 4: AI Maturity, Predictive Preparedness, and Resilience Stratification

Discussion

The evidence indicates that AI reshapes dynamic capabilities asymmetrically across the sensing–seizing–transforming triad. Prior to AI integration, sensing in the hospitality supply network was largely experiential and relational, grounded in managerial vigilance and supplier communication, consistent with Teece's (2007) cognition-centered microfoundations. AI integration introduced a structural shift: predictive analytics, real-time dashboards, and automated anomaly detection embedded intelligence directly into operational infrastructures. This finding resonates with Warner and Wäger's (2019) argument that digital technologies reconfigure dynamic capabilities by infrastructurally embedding intelligence.

With respect to seizing, AI enhanced coordination speed through route optimization, forecasting adjustments, and real-time inventory alignment, consistent with Belhadi et al.'s (2021) assertion that analytics improve supply chain responsiveness. However, unlike manufacturing-based studies that

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associate AI adoption with radical reconfiguration (Ivanov, 2021), hospitality actors largely experienced acceleration rather than reinvention. Seizing remained anchored in established buffering mechanisms.

The transforming dimension exhibited the most limited development. Participants described incremental automation constrained by governance concerns, data privacy risks, and workforce implications, aligning with research emphasizing institutional and socio-technical barriers to digital transformation (Warner & Wäger, 2019; Dubey et al., 2023). The organizational culture and workforce readiness of hospitality firms appear as important moderators of the relationship between AI adoption and capability development, a dimension that warrants greater attention in future research.

The cross-tier distribution of AI-enabled capabilities further complicates firm-centric interpretations of DCT. Sensing intensity was concentrated upstream, particularly among national distributors with deeply integrated analytics infrastructures. Hotel actors remained partially dependent on supplier-generated intelligence. This pattern extends ecosystem-based strategy research (Adner & Kapoor, 2010) by demonstrating that adaptive capacity in service supply networks is relationally configured rather than symmetrically embedded within focal firms.

Moreover, the seizing and transforming dimensions require clearer operational distinction. Seizing, in the present findings, refers to the operationalization and acceleration of resource orchestration through AI-enabled optimization, refining existing decision routines and improving coordination speed. Transforming, by contrast, entails deeper governance reconfiguration, structural redesign, and reallocation of decision rights. In hospitality supply networks, seizing was moderately enhanced through route optimization and forecasting tools, while transforming remained constrained because it requires institutional realignment and trust recalibration that extend beyond technological adoption.

Taken together, the findings demonstrate that AI functions primarily as a capability amplifier. It disproportionately strengthens sensing, moderately enhances seizing, and only gradually advances transforming, yielding layered, asymmetric, and relationally distributed resilience in service-intensive hospitality supply ecosystems.

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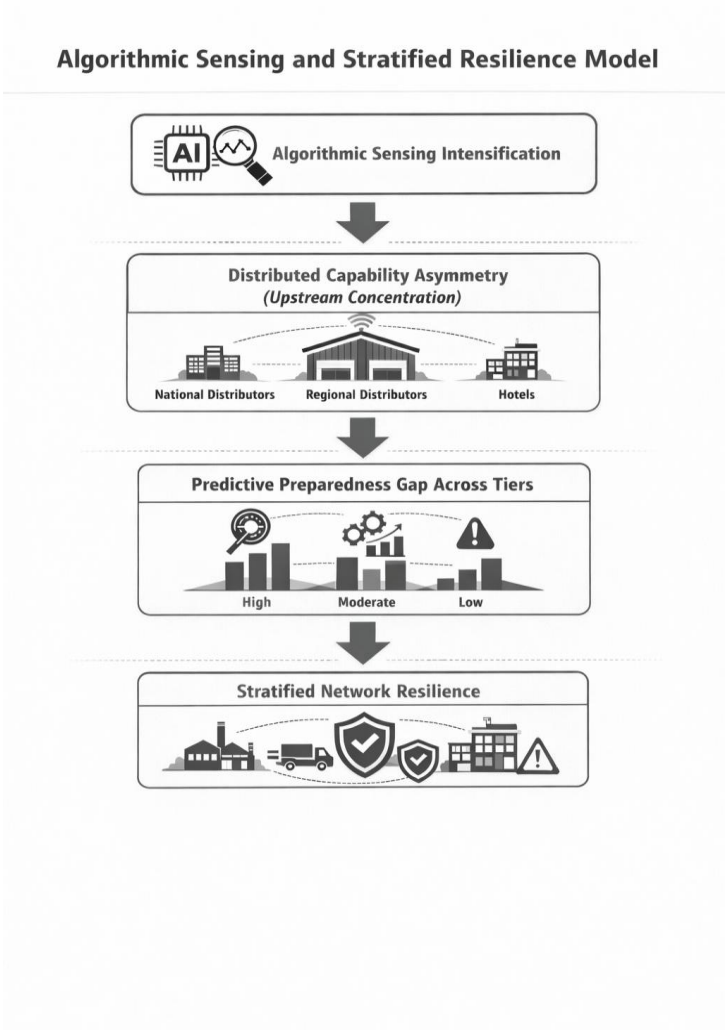


Figure 2: Algorithmic Sensing and Stratified Resilience Model. Source: Author's own illustration.

The figure 2 above illustrates how AI-driven sensing amplification generates distributed capability asymmetry across supply tiers, producing stratified resilience outcomes while structural transformation remains staged and institutionally constrained.

Conclusion

Summary

This study examined how AI-enabled technologies contribute to supply chain resilience within the U.S. hospitality sector, anchored in Dynamic Capabilities Theory. Drawing on qualitative data from ten supply chain professionals across a multi-tier hospitality supply network, the findings reveal that AI reshapes dynamic capabilities asymmetrically: disproportionately amplifying sensing through algorithmic

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forecasting and real-time analytics, moderately enhancing seizing through operational acceleration, and only incrementally advancing transforming due to governance constraints and institutional inertia. Capability development is uneven across supply tiers, with upstream distributors exhibiting stronger AI-enabled sensing than hotel actors, producing distributed capability asymmetry and relationally dependent resilience outcomes.

Theoretical Implications and Further Research

The study contributes three boundary refinements to DCT. First, sensing in digitally mediated ecosystems becomes partially infrastructural rather than exclusively cognitive—co-produced by computational architectures and managerial interpretation. Second, capability location shifts from firm-bound to relationally distributed across supply tiers. Third, capability evolution becomes temporally imbalanced, with sensing accelerating faster than transforming. These refinements extend DCT's applicability to ecosystem-based, algorithmically embedded service environments.

Several directions for further research emerge. Future studies should employ comparative multi-case designs across hospitality segments and geographic regions to assess generalizability. Longitudinal research could examine whether incremental automation ultimately leads to deeper governance redesign or whether institutional constraints persist. Quantitative network analysis could formally model whether resilience is constrained by the least digitally mature node. Additionally, future research should more deeply theorize the role of organizational culture, workforce readiness, and regulatory frameworks in moderating the relationship between AI adoption and capability development. Exploration of complementary digital technologies, blockchain, IoT, and advanced ERP integrations would further enrich understanding of AI-enabled resilience trajectories.

Practical Implications

Managers in hospitality supply networks should reconceptualize resilience as a digitally mediated and relational capability. AI should be treated primarily as a sensing infrastructure rather than a standalone transformation tool. Hotel procurement leaders should prioritize investments in data integration, forecasting interoperability, and analytics literacy. Resilience must be managed at the ecosystem level: digital capability audits of key suppliers and ecosystem partnership strategies should complement traditional cost and quality criteria. Managers should differentiate structural redundancy from adaptive capability and design phased digital roadmaps aligned with governance adaptation and workforce training. Clear data governance frameworks and transparent communication about AI augmentation are essential for sustaining adaptive momentum.

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Appendix A: Coding Tree

Stage 1: First-Order In Vivo Codes (52 total; illustrative examples)	**Stage 2: Second-Order Themes (14 Categories)**	**Aggregate Theoretical Dimensions (6)**
"Buffer stock"	Redundancy-Based Mitigation	Redundancy-Based Structural Seizing

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Stage 1: First-Order In Vivo Codes (52 total; illustrative examples)	**Stage 2: Second-Order Themes (14 Categories)**	**Aggregate Theoretical Dimensions (6)**
"Multiple suppliers"	Redundancy-Based Mitigation	Redundancy-Based Structural Seizing
"Managing purchase orders"	Procurement Oversight Routines	Redundancy-Based Structural Seizing
"Inventory continuity"	Procurement Oversight Routines	Redundancy-Based Structural Seizing
"Unpredictable demand"	Demand Volatility Exposure	Algorithmic Sensing Intensification
"Weather disruptions"	Demand Volatility Exposure	Algorithmic Sensing Intensification
"Real-time dashboards"	Real-Time Visibility Enhancement	Algorithmic Sensing Intensification
"Predictive analytics"	Algorithmic Forecasting Integration	Algorithmic Sensing Intensification
"Route optimization"	Operational Acceleration via AI	Algorithmic Sensing Intensification
"Anomaly detection alerts"	Algorithmic Forecasting Integration	Algorithmic Sensing Intensification
"Depend on supplier forecasts"	Dependent Hotel-Level Sensing	Distributed Capability Asymmetry
"Upstream systems fully integrated"	Upstream Analytics Dominance	Distributed Capability Asymmetry

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Stage 1: First-Order In Vivo Codes (52 total; illustrative examples)	**Stage 2: Second-Order Themes (14 Categories)**	**Aggregate Theoretical Dimensions (6)**
"Limited in-house analytics"	Dependent Hotel-Level Sensing	Distributed Capability Asymmetry
"Automation speeds deliveries"	Operational Acceleration via AI	Predictive Preparedness Gradient
"Early shortage detection"	Predictive Preparedness	Predictive Preparedness Gradient
"We can redirect inventory"	Predictive Preparedness	Predictive Preparedness Gradient
"Over-reliance on technology"	Governance Caution	Temporally Imbalanced Transformation
"Managerial approval required"	Governance Caution	Temporally Imbalanced Transformation
"Data privacy concerns"	Governance Caution	Temporally Imbalanced Transformation
"Cost of implementation"	Infrastructure Constraints	Capability Stratification
"Lack of skilled personnel"	Workforce Skill Gaps	Capability Stratification
"Gradual system integration"	Incremental Transformation	Temporally Imbalanced Transformation
"Automation without redesign"	Incremental Transformation	Temporally Imbalanced Transformation

Table A1: Multi-Stage Coding Structure