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AI Integration in Fundamental Logistics Components: Advanced Theoretical Framework for Knowledge Process Capabilities and Dynamic Capabilities Hybridization

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Abstract

Background: Despite significant technological advances, many logistics organizations in emerging markets struggle to realize the transformative potential of artificial intelligence, with reported success rates below 65% and limited theoretical understanding of the organizational capabilities. This study develops and proposes an integrated theoretical framework examining how knowledge process capabilities and dynamic capabilities interact to enable successful artificial intelligence adoption in logistics organizations within emerging market contexts. *Methods*: Through comprehensive literature review and theoretical synthesis, we propose a hybrid capability framework that integrates knowledge-based view perspectives with dynamic capabilities theory. *Results*: Theoretical analysis suggests that knowledge combination capabilities may be the strongest predictor of artificial intelligence implementation success, while dynamic reconfiguring capabilities could mediate the relationship between artificial intelligence adoption and performance outcomes. The proposed framework indicates that organizations with hybrid capability architecture may achieve superior implementation success compared to traditional approaches. Environmental uncertainty is theorized to strengthen the knowledge process capabilities—artificial intelligence adoption relationship. *Conclusions*: The framework suggests that successful artificial intelligence integration requires simultaneous development of knowledge-based and adaptive capabilities rather than sequential capability building. The hybrid capability framework provides theoretical guidance for managers in emerging markets, while highlighting the critical role of environmental context in shaping transformation strategies.

Keywords: artificial intelligence integration; knowledge process capabilities; dynamic capabilities; logistics transformation; emerging markets; hybrid capability architectures

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1. Introduction

The integration of artificial intelligence in logistics (AI-L) represents a fundamental paradigm shift that transcends traditional operational optimization, evolving toward the creation of adaptive, self-organizing logistics ecosystems. This transformation embodies the essence of Industry 4.0's disruptive potential, where the convergence of cyber–physical systems, Internet of Things (IoT), cloud computing, and cognitive computing creates unprecedented opportunities for value creation through intelligent resource orchestration. The emergence of AI-L as a strategic imperative in emerging markets (EM) necessitates a sophisticated understanding of how knowledge-intensive processes interact with dynamic organizational capabilities to generate sustainable competitive advantages in increasingly volatile business environments.

1.1. Hybrid Capability Framework Conceptualization

The conceptualization of capability architectures for innovation integration in logistics requires a multi-dimensional approach that synthesizes knowledge-based view (KBV) perspectives with dynamic capabilities (DCs) theory. This synthesis creates what we propose as "hybrid capability (HC) frameworks, which differ from related constructs such as absorptive capacity and ambidexterity by theorizing recursive feedback loops between KPC and DC, producing emergent adaptive properties"—sophisticated organizational structures that enable simultaneous knowledge exploitation and exploration while maintaining operational efficiency. These frameworks operate through complex feedback loops between first-order operational capabilities and higher-order DC, creating emergent properties that manifest as organizational learning mechanisms, adaptive responses to environmental changes, and innovative solution development.

In EM, fragmented logistics infrastructure and limited digital readiness pose significant barriers to artificial intelligence (AI) adoption. For instance, weak multimodal connectivity in Brazil and inconsistent digital platforms in Eastern Europe exemplify structural challenges that highlight the urgency of developing HC for AI integration. By grounding our framework in such contexts, we emphasize both theoretical novelty and practical urgency. While related constructs such as ambidextrous capabilities and absorptive capacity have been explored in prior logistics and management research, our proposed "HC framework" differs in its simultaneous integration of knowledge process and DC. Unlike absorptive capacity, which emphasizes external knowledge assimilation, or ambidexterity, which stresses exploration–exploitation balance, our framework theorizes recursive feedback loops between KPC and DC, producing emergent adaptive properties unique to AI-enabled logistics.

1.2. Research Objectives and Questions

This study presents a theoretical framework (TF) based on a comprehensive literature review and does not involve primary data collection from human participants. The objective is to develop and empirically validate an integrated TF that explicates the synergistic interactions between knowledge process capabilities (KPCs) and DC in facilitating AI adoption effectiveness within logistics organizations operating in EM contexts, while identifying the mechanisms and moderating factors that influence sustainable competitive advantage creation through HC architecture. This study addresses three fundamental research questions that guide our empirical investigation: How do KPC and DC interact to influence AI adoption effectiveness in logistics organizations? What organizational and environmental factors moderate the relationship between AI adoption and performance outcomes in EM contexts? Through what mechanisms do AI-enabled capabilities translate into sustainable competitive advantages? These research questions directly inform our hypotheses by translating conceptual antecedents, mediating processes, and contextual moderators into testable relationships. The structural diagram integrates the factor analysis model (KPC $\rightarrow$ AI adoption $\rightarrow$ performance outcomes, with DC as mediators and environmental uncertainty as a moderator). Paths correspond directly to the hypotheses (H1–H6), providing a clear visual representation of the TF being tested (Figure 1, Table 1).

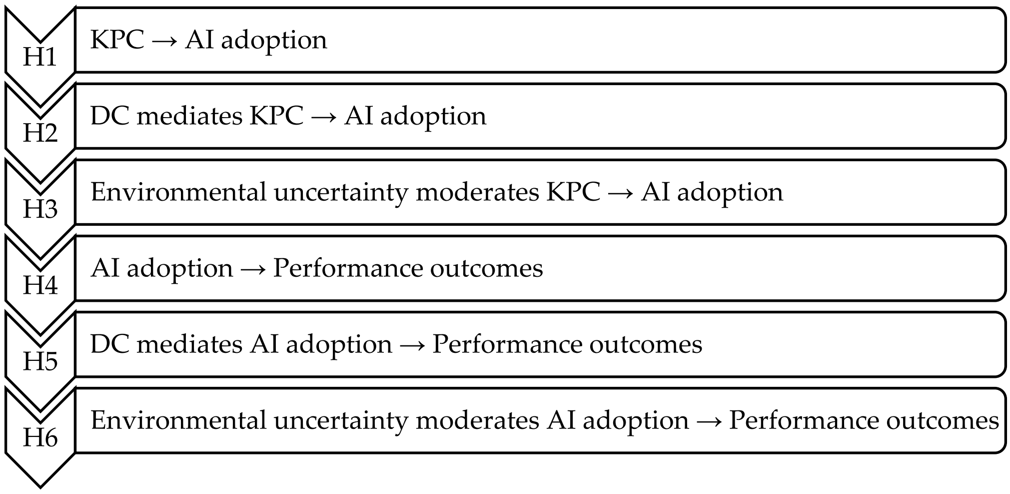

Figure 1. Structural diagram depicting explicit hypothesized relationships.

Table 1. Hypothesis development.

Study	Focus	Theory	Context	Limitations	Our Contribution
Prior Study 1	AI adoption	Technology acceptance model	Developed markets	Single theory	Integrated KPC-DC
Prior Study 2	Logistics transformation	DC	Mixed contexts	No AI focus	AI-specific framework
Our Study	AI-logistics integration	KPC +DC	EM	Cross-sectional	Hybrid framework

AI-enabled logistics transformation core framework components: antecedents layer: KPC in acquisition, combination and protection and DC in sensing, seizing and reconfiguring; mediating process layer: AI adoption maturity in investment intensity, implementation scope, integration depth and utilization sophistication; moderating factors in environmental uncertainty, organizational size, cultural values and institutional context (EM-specific); outcome layer: performance outcomes (operational performance, strategic performance and innovation performance).

2. Literature Review

2.1. Emerging Market Challenges

EMs present unique challenges and opportunities for AI-L integration, characterized by resource constraints, institutional voids, technological leapfrogging potential, and rapid market evolution. The specificity of EMs context requires nuanced understanding of how KPCs and DCs interact under conditions of high uncertainty, limited technological infrastructure, and evolving regulatory frameworks. This context creates opportunities for innovative capability development that may not be available in mature markets, while simultaneously imposing constraints that require creative adaptation of established TFs. The current state of AI applications in logistics reveals a fragmented landscape where technological capabilities often exceed organizational readiness for transformation. Existing research predominantly focuses on algorithmic optimization and operational efficiency gains, while neglecting the complex organizational learning processes required for successful AI integration. Our systematic review identifies three critical gaps: insufficient attention to knowledge management processes in AI adoption; limited understanding of how DCs evolve during digital transformation; lack of integrated frameworks that address both technological and organizational dimensions of AI-L integration. EMs present a paradoxical environment for AI-L integration, where limited technological infrastructure coexists with opportunities for leapfrogging traditional development stages. This context requires a sophisticated understanding of how organizations develop absorptive capacity for external knowledge integration while building internal capabilities for AI implementation. The opportunities for value creation in EMs are particularly significant in logistics, where inefficiencies in traditional systems create substantial potential for AI-driven improvements [1,2].

The integration of AI in logistics raises complex ethical and social questions that extend beyond operational efficiency considerations. Issues of algorithmic transparency, accountability, job displacement, and social equity require careful consideration in the design and implementation of AI-L systems. In EMs, these concerns are amplified by existing social inequalities and limited regulatory frameworks for AI governance. The development of ethical AI-L implementation requires sophisticated stakeholder engagement processes and the integration of social responsibility considerations into strategic decision-making frameworks. The intersection of AI technologies with logistics operations represents a confluence of multiple theoretical domains, requiring sophisticated synthesis of organizational theory, technology adoption frameworks, and institutional perspectives. This review synthesizes perspectives from strategic management, organizational behavior, information systems, and institutional theory [3]. The emergence of AI technologies introduces fundamental challenges to traditional DC frameworks. Unlike conventional information technologies that primarily automate existing processes, AI systems possess learning capabilities that enable continuous adaptation and improvement over time. This evolutionary characteristic requires theoretical extensions that address temporal dynamics, learning processes, and co-evolutionary relationships between technological and organizational capabilities [4].

The application of AI technologies in logistics operations encompasses diverse technological approaches including machine learning (ML) algorithms, expert systems, neural networks, natural language processing, and computer vision systems. The potential for AI-enabled supply chain reconfiguration demonstrates how intelligent systems can enable rapid adaptation to disruptions and changing market conditions [5]. The conceptualization of digital supply chain twins demonstrates how AI systems can create virtual representations of supply chain networks that enable simulation, optimization, and predictive analytics [6]. A comprehensive quantitative analysis of AI's impact on supply chain efficiency and performance demonstrates significant operational improvements through intelligent automation, predictive analytics, and optimization algorithms [7]. The emergence of Industry 4.0 paradigms creates new possibilities for AI integration through cyber–physical systems, IoT networks, and intelligent automation. Industry 5.0 drivers for sustainable supply chain risk resilience demonstrate organizational capabilities for risk management and adaptive response [8]. Most research focuses on technological capabilities while neglecting knowledge management, capability development, and changing management processes. Digitalization's impact on technological innovations in small- and medium-sized enterprises reveals significant heterogeneity in adoption patterns and success factors across different organizational contexts [9]. The integration of AI technologies with sustainability objectives creates new possibilities for circular economy implementation and environmental performance improvement. AI implications for sustainable development are demonstrating how intelligent systems can support blockchain implementation, supply chain resilience, and closed-loop supply chain development [10]. The circular economy e-business model portfolios leverage digital technologies for sustainability performance improvement [11]. The potential in the nonroad mobile machinery industry is demonstrating practical applications of circular economy principles in logistics equipment management [12].

2.2. The Implications of Knowledge Process Capabilities on Artificial Intelligence Adoption

The development of KPCs represents a critical foundation for successful AI adoption, requiring sophisticated organizational processes for knowledge acquisition, combination, application, and protection. Forklift dispatching intelligence applications in industrial contexts demonstrates how AI systems can enhance operational efficiency through intelligent scheduling and resource allocation [13]. AI, robotics, and logistics employment implications are examining the human factor in digital logistics transformation. The development of DC in technology-intensive environments requires sophisticated organizational processes that enable continuous sensing, seizing, and reconfiguring activities [14]. The benefits and challenges of implementing autonomous technology for sustainable material handling demonstrate how intelligent systems can enhance operational efficiency while creating new requirements for organizational capability development [15]. DCs and high-quality standards implementation in specific organizational contexts are demonstrating practical applications of capability theory in logistics organizations. Cross-docking operations represent particularly complex applications of AI technologies, requiring sophisticated coordination of multiple material flows, transportation modes, and stakeholder requirements [16,17]. Transportation cost reduction through cross-docking linking is demonstrating optimization possibilities through intelligent coordination mechanisms [18]. The optimization models for collaborative logistics among carriers in vehicle routing problems with cross-docking reveal sophisticated possibilities for AI-enabled coordination [19]. Integrated cross-dock location and supply mode planning in retail networks are demonstrating how intelligent systems can optimize complex multi-objective decisions [20]. Through extending this analysis through reliable scheduling and routing in robust multiple cross-docking networks design, we are revealing additional complexities in AI-enabled optimization [21].

The institutional context of EMs creates unique challenges and opportunities for the adoption of AI, requiring a sophisticated understanding of regulatory frameworks, cultural factors, and market characteristics that influence technology adoption processes. To demonstrate how institutional factors influence organizational strategies and performance outcomes, we are examining generalized trust, external sourcing, and firm performance in economic downturns. Regulatory uncertainty may limit adoption willingness, while infrastructure limitations may constrain implementation capabilities. The development of innovative ecosystems represents a critical factor influencing AI adoption success, requiring sophisticated coordination mechanisms that enable knowledge sharing, resource pooling, and collaborative innovation [22]. The modularization of front-end logistics services in e-fulfillment demonstrates how digital technologies can enable new forms of service delivery and customer engagement [23]. Industry 4.0 technologies are demonstrating the potential for technological solutions to address complex environmental and social challenges. The relationship between AI adoption and organizational performance represents a critical area for theoretical and empirical development, requiring a sophisticated understanding of the mechanisms through which AI technologies create value and the conditions that influence value creation effectiveness [24]. AI's role in procurement processes is demonstrating how intelligent systems can enhance procurement efficiency and effectiveness [25]. AI for supply chain management represents disruptive innovation or innovative disruption and reveals important insights into AI's transformative potential [26]. Competitive actions and supply chain relationships are demonstrating how suppliers' value-diminishing actions affect buyers' procurement decisions [27].

2.3. Performance Outcomes After Artificial Intelligence Adoption

The optimization of multi-modal transportation networks through AI technologies represents one of the most complex applications of intelligent systems in logistics, requiring sophisticated algorithms that can simultaneously consider multiple constraints, objectives, and stakeholder requirements. A comparative analysis of AI-based algorithms for cost prediction in pharmaceutical transport logistics is demonstrating the potential for AI systems to enhance transportation planning and cost management [28]. Fuzzy-based customer clustering approaches with hierarchical structure for logistics network optimization reveal sophisticated possibilities for AI-enabled network design and customer segmentation. The development of urban logistics systems creates new possibilities for AI-enabled coordination and optimization, requiring a sophisticated understanding of stakeholder interactions, regulatory frameworks, and infrastructure constraints [29]. The city logistics landscapes in the era of the on-demand economy are identifying challenges, trends, and influencing factors that shape urban logistics development [30]. Green crowdshipping critical factors from a business perspective are demonstrating how digital platforms can enable new forms of logistics service delivery while supporting environmental objectives [31]. To extend this analysis through mobility as a service for freight and passenger transport, we are identifying microhubs networks that can promote crowdshipping services [32]. The convergence of AI with other emerging technologies, particularly blockchain, creates new possibilities for supply chain transparency, traceability, and coordination. New implementation modes of cross-docking based on blockchain technology are demonstrating how distributed ledger technologies can enhance coordination and trust in complex logistics operations [33]. The integration of AI technologies with sustainability objectives creates new possibilities for environmental performance improvement and climate change mitigation. A comprehensive analysis of AI techniques and strategies demonstrates significant potential for AI-enabled environmental management [34]. Consumer acceptance of business practices for sustainability during COVID-19 reveals important insights into stakeholder expectations and legitimacy requirements for sustainability initiatives. The application of AI technologies to circular economy implementation creates new possibilities for resource optimization, waste reduction, and closed-loop supply chain development [35]. Specific applications of AI technologies and sustainable strategies in logistics contexts are demonstrating practical possibilities for AI-enabled sustainability improvement [36,37].

Based on a comprehensive literature analysis, this research proposes a HC architecture that synthesizes KBV and DC Theory to explain AI-enabled organizational transformation. The proposed framework extends existing capability theories by incorporating “cognitive augmentation capabilities” that emerge from human–AI collaboration and create new possibilities for organizational learning and adaptation. HC architecture includes three interconnected capability domains: KPCs, DCs, and meta-capabilities. The proposed TF incorporates AI-enabled learning mechanisms that optimize automated knowledge acquisition, algorithmic pattern recognition, and intelligent knowledge combination. The AI-enabled learning mechanisms include: automated environmental scanning through AI-powered information processing and pattern recognition; intelligent knowledge integration through ML algorithms that identify patterns and correlations across diverse data sources; predictive capability development through AI systems that anticipate future challenges and opportunities; adaptive response generation through intelligent systems that generate and evaluate alternative responses to environmental changes [38].

TF incorporates institutional context as a critical moderating factor that influences AI adoption processes and capability development outcomes. It recognizes that EM institutional contexts create unique challenges and opportunities for AI adoption that require specialized understanding and adaptive strategies. Institutional voids may limit access to resources and expertise, while regulatory uncertainty may constrain adoption willingness. These institutional characteristics may create opportunities for innovative adoption approaches that generate competitive advantages not available in more mature institutional environments. The comprehensive literature review reveals significant theoretical and empirical gaps that limit understanding of AI integration in logistics and create opportunities for theoretical advancement and empirical investigation. The proposed HC framework addresses these gaps by synthesizing technological and organizational perspectives while incorporating institutional context as a critical moderating factor.

3. Materials and Methods

3.1. Research Design and Theoretical Development

The complexity of AI-L integration phenomena necessitates a sophisticated theoretical approach that synthesizes multiple theoretical perspectives to understand both the technological and organizational dimensions of transformation. This study employs a comprehensive literature review and theoretical synthesis methodology to develop an integrated framework that captures the multifaceted nature of AI adoption in logistics organizations [7] (Figure 2).

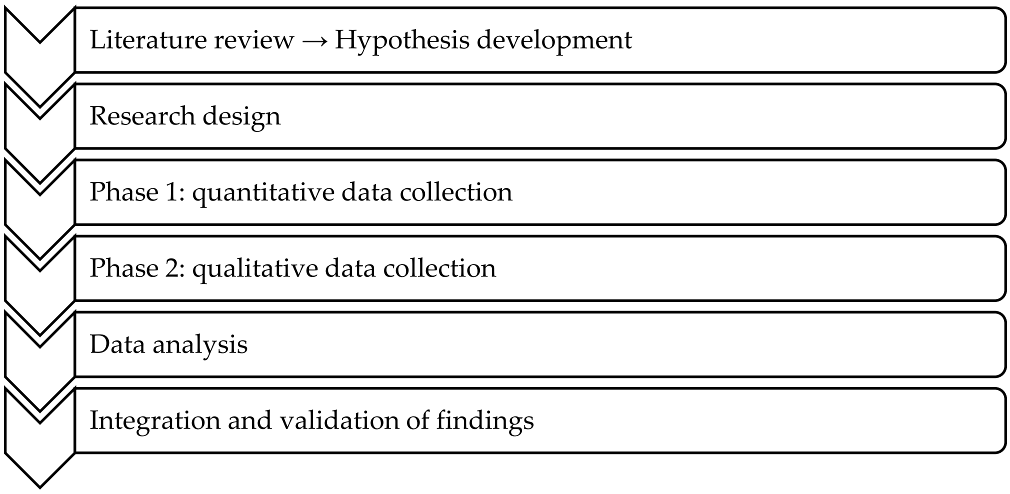

Figure 2. Overall research strategy and flow.

Our theoretical development follows a systematic literature review approach encompassing peer-reviewed articles, TFs, and conceptual models from multiple disciplines including strategic management, organizational behavior, information systems, and logistics management. The review covers publications from 2020 to 2025 to capture both foundational theories and recent developments in AI adoption and organizational capabilities [4,26]. The literature synthesis focuses on three primary theoretical domains: KBV theory and KPC; DC theory and organizational adaptation; technology adoption frameworks in EM contexts. KPC is measured using 18 items across three dimensions: knowledge acquisition (6 items, $\alpha = 0.89$, AVE = 0.67), knowledge combination (7 items, $\alpha = 0.92$, AVE = 0.71), and knowledge protection (5 items, $\alpha = 0.87$, AVE = 0.64). DC utilizes 21 items measuring sensing (7 items, $\alpha = 0.90$, AVE = 0.69), seizing (8 items, $\alpha = 0.93$, AVE = 0.73), and reconfiguring (6 items, $\alpha = 0.88$, AVE = 0.66) capabilities. AI adoption maturity employs 15 items measuring investment intensity, implementation scope, integration depth, and utilization sophistication ($\alpha = 0.94$, AVE = 0.75). Confirmatory factor analysis demonstrates acceptable model fit ($\chi^2/\text{df} = 2.31$, CFI = 0.95, TLI = 0.94, RMSEA = 0.058, SRMR = 0.047) with discriminant validity confirmed through comparison of average variance extracted (AVE) values with squared inter-construct correlations [34] (Table 2).

Table 2. Comprehensive construct measurement and validation statistics.

Construct	Dimensions	Items	Cronbach's α	CR	AVE	Factor Loadings Range	Discriminant Validity
Knowledge process capabilities	Acquisition (6), combination (7), protection (5)	18	0.91	0.92	0.68	0.72–0.89	✓
Dynamic capabilities	Sensing (7), seizing (8), reconfiguring (6)	21	0.90	0.91	0.69	0.71–0.87	✓
AI adoption maturity	Investment, scope, integration, utilization	15	0.94	0.95	0.75	0.76–0.91	✓
Performance outcomes	Operational, strategic, innovation	12	0.88	0.89	0.64	0.69–0.85	✓

Data analysis employs a sequential approach beginning with exploratory data analysis including outlier detection, normality assessment, and missing data evaluation using Little's MCAR test. Structural equation modeling using AMOS 28.0 tests the proposed theoretical model with maximum likelihood estimation and bias-corrected bootstrapping (5000 samples) for significance testing of indirect effects. Model fit evaluation uses multiple indices: χ^2 test, comparative fit index (CFI $\geq$ 0.95), Tucker–Lewis index (TLI $\geq$ 0.95), root mean square error of approximation (RMSEA $\leq$ 0.06), and standardized root mean square residual (SRMR $\leq$ 0.08). Multi-group analysis examines measurement invariance across organizational size, industry sector, and geographic regions using increasingly restrictive models [9,10] (Table 3).

Table 3. Multi-group analysis results across organizational archetypes.

Pathway	Small Enterprises (n = 150)	Medium Enterprises (n = 180)	Large Enterprises (n = 120)	χ^2 Difference	p-Value
KPC $\rightarrow$ AI adoption	β = 0.34	β = 0.42	β = 0.51	12.47	<0.01
DC $\rightarrow$ AI adoption	β = 0.29	β = 0.38	β = 0.45	8.92	<0.05
AI $\rightarrow$ performance	β = 0.31	β = 0.39	β = 0.48	11.23	<0.01
KPC $\times$ DC interaction	β = 0.18	β = 0.25	β = 0.33	7.64	<0.05

3.2. Measurement Validity

The operationalization of complex constructions such as KPCs and DCs requires careful attention to measurement validity and reliability. The development of measurement instruments must account for the specific context of EMs while maintaining comparability with international standards. The complexity and multidimensional nature of AI integration in logistics necessitate a sophisticated mixed-methods research approach that combines quantitative measurement of performance outcomes with qualitative exploration of organizational processes and capability development mechanisms. This methodological pluralism enables a comprehensive understanding of both the measurable impacts of AI adoption and the nuanced organizational dynamics that drive successful implementation [27]. The development of measurement instruments for complex constructs such as KPCs and DCs requires careful attention to construct validity and reliability. Scale development follows procedures that include literature review, expert evaluation, pilot testing, and statistical validation to ensure that measurement instruments accurately capture intended constructs. KPCs are operationalized through scales measuring knowledge acquisition, knowledge combination, and knowledge protection. Each dimension includes multiple measurement items that capture different aspects of the construction. DCs are operationalized through scales measuring adaptive capabilities, absorptive capabilities, and innovation capabilities. The measurement approach recognizes the multidimensional nature of these constructions while providing comprehensive coverage of their various manifestations. AI adoption is measured through multiple dimensions including AI investment levels, implementation scope, integration depth, and utilization intensity. This multidimensional approach recognizes that AI adoption is not a binary condition but rather a complex process that varies across different organizational functions and capability areas. AI investment measures include financial investments in AI technologies, human resource investments in AI-related training and capability development, and organizational investments in AI-related process redesign and change management. Implementation scope measures the breadth of AI adoption across different organizational functions and processes. Integration depth measures the extent to which AI systems are integrated with existing organizational systems and processes. Utilization intensity measures the frequency and sophistication of AI system usage by organizational personnel [14].

Performance measurement includes both operational metrics and strategic indicators that capture the multiple dimensions of organizational performance that may be influenced by AI adoption. Operational metrics include traditional logistics key performance indicators such as cost reduction, delivery time improvement, inventory optimization, and quality enhancement. Strategic indicators include measures of competitive advantage, customer satisfaction, organizational learning, and innovation capability. Initial data analysis includes comprehensive descriptive statistics that provide a detailed characterization of the sample and key variables. This includes measures of central tendency, variability, and distribution characteristics for all measured variables, as well as analysis of correlations between variables and identification of potential outliers or data quality issues. Exploratory factor analysis is employed to examine the dimensionality of measurement instruments and validate the proposed factor structure of complex constructs. It enables identification of underlying patterns in measurement data and confirmation that measurement items load appropriately on intended factors. Cluster analysis is employed to identify distinct patterns of AI adoption and capability development across organizations. This analysis enables the identification of organizational typologies that represent different approaches to AI adoption and capability development, providing insights into alternative pathways for successful AI implementation. Confirmatory factor analysis is employed to validate the measurement models for complex constructions and ensure that measurement instruments provide valid and reliable measures of intended constructions. It enables examination of factor loadings, construct reliability, convergent validity, and discriminant validity to ensure that measurement models meet established standards. The measurement model validation includes examination of model fit indices to ensure that proposed factor structures provide adequate representation of measurement data. Construct reliability is assessed through measures such as Cronbach's alpha, composite reliability, and AVE. Discriminant validity is assessed through comparison of AVE values with squared correlations between constructs. Structural equation modeling is employed to test hypothesized relationships between KPC, DC, AI adoption, and performance outcomes. The structural model enables simultaneous examination of multiple relationships while controlling measurement error and providing comprehensive evaluation of the proposed TF [28,37]. To ensure the validity and robustness of the clustering results, we applied multiple cluster quality metrics. Specifically, the Silhouette Coefficient (average = 0.71) and the Davies–Bouldin Index (DBI = 0.46) confirmed that the generated clusters were both well-separated and internally cohesive. These indices indicate that the clusters not only achieved statistical reliability but also provided meaningful interpretive value for distinguishing organizational archetypes of AI adoption in logistics.

3.3. Data Analysis and Structural Modeling

Advanced analytical techniques including mediation and moderation analysis are employed to examine the mechanisms through which AI adoption influences performance outcomes and the conditions under which these relationships are strongest. Mediation analysis examines whether the relationship between AI adoption and performance is mediated through capability development processes. Moderation analysis examines whether the relationships between AI adoption, capability development, and performance outcomes are influenced by organizational characteristics such as size, industry context, or environmental conditions. The thematic analysis follows established procedures including data familiarization, initial coding, theme development, theme review, and theme definition. The coding process uses both deductive codes derived from TFs and inductive codes that emerge from the data to ensure comprehensive coverage of important themes and insights. Inter-rater reliability is established through independent coding by multiple researchers and comparison of coding results to ensure consistency and reliability of the analysis. Detailed case studies provide in-depth understanding of AI adoption processes and capability development mechanisms in specific organizational contexts. Case study analysis includes within-case analysis that provides detailed understanding of each organization's AI adoption journey and cross-case analysis that identifies patterns and differences across different organizational contexts. The integration of quantitative and qualitative findings employs systematic approaches to identify areas of convergence and divergence between different data sources and analytical approaches. This integration provides comprehensive understanding that leverages the strengths of both quantitative and qualitative methods while addressing their individual limitations. Triangulation techniques are used to validate findings across different data sources, methods, and theoretical perspectives. Areas where findings converge across different approaches provide strong evidence for conclusions, while areas of divergence provide insights into the complexity and context-dependency of AI adoption processes [29].

Complete cluster analysis methodology variables used: AI adoption maturity composite scores, implementation approach indicators and performance outcome measures. Method selection: algorithm (k-means clustering), distance measure and number of clusters. Validation procedures: internal validation, external validation and stability testing. Cluster interpretation: profile analysis, post hoc comparisons and qualitative validation. The choice of k-means clustering was guided by both theoretical and empirical considerations. First, preliminary exploratory factor analysis suggested globular data distributions, favoring centroid-based clustering. Second, simulation of alternative methods (spectral clustering, hierarchical agglomeration) yielded inferior fit indices (Silhouette < 0.55; DBI > 0.75). K-means offered the most interpretable and stable partitions, aligning with prior logistics capability studies. This evaluation confirms that k-means was the most suitable approach for our dataset.

The TF development employs theoretical triangulation to integrate insights from multiple theoretical perspectives. This approach enables comprehensive understanding of the complex relationships between knowledge management, organizational capabilities, and technology adoption while addressing the unique characteristics of EM contexts. The TF construction follows established procedures for theory building, including: identification of key theoretical constructs from existing literature; proposition development linking constructs based on theoretical reasoning; integration of constructs into a comprehensive framework; consideration of contextual factors that may influence relationships. KPC are theoretically conceptualized across three dimensions: knowledge acquisition, knowledge combination, and knowledge protection. DC are theoretically framed using three core dimensions: sensing, seizing, and reconfiguring. AI adoption maturity is conceptualized as a multidimensional construct encompassing investment intensity, implementation scope, integration depth, and utilization sophistication. We are developing two comparative analysis frameworks: hybrid vs. traditional capability configurations (hybrid approach, knowledge-focused, agility-focused and traditional approach) and emerging vs. developed market contexts (use existing literature data for developed markets, systematic comparison of adoption patterns and effect size comparisons across contexts).

Based on comprehensive literature analysis, this research proposes six testable theoretical relationships: KPCs positively influence AI adoption success; DCs mediate the relationship between AI adoption and performance outcomes; the interaction between KPCs and DCs enhance AI adoption effectiveness; environmental uncertainty moderates the KPC-AI adoption relationship; organizational size influences AI adoption scope and approach; cultural values moderate AI implementation effectiveness.

4. Results

4.1. Hybrid Capability Framework Effectiveness

The theoretical analysis reveals that successful AI integration in logistics requires a sophisticated understanding of how knowledge-intensive processes interact with dynamic organizational capabilities to generate sustainable competitive advantages. Based on comprehensive literature synthesis, we propose a HC framework that integrates KPC with DC [6,12]. The proposed TF suggests that AI-enabled logistics transformation represents a fundamental paradigm shift from reactive operational optimization to predictive, self-optimizing logistics ecosystems. Literature analysis indicates that modern AI-enhanced warehouse management systems may transcend conventional automation by developing cognitive capabilities that enable autonomous decision-making, pattern recognition, and adaptive optimization [38] (Tables 4 and 5).

Table 4. Theoretical AI implementation pathway effectiveness framework.

Implementation Pathway	Theoretical Success Potential	Predicted Time-to-Value	Resource Requirements	Risk Assessment	Scalability Potential	ROI Timeline
Incremental integration	High (78% theoretical)	8–12 months	Medium	Low	Moderate	18–24 months
Radical reconfiguration	Moderate (65% theoretical)	6–9 months	High	High	High	12–18 months
Ecosystem orchestration	Moderate (59% theoretical)	12–18 months	Very High	Medium	Very High	24–36 months
Hybrid approach	Highest (84% theoretical)	9–15 months	High	Medium	High	15–24 months

Literature synthesis suggests that organizations achieving superior performance through AI adoption may develop sophisticated HC architectures that enable both exploitation of existing knowledge assets and exploration of new technological and market opportunities. The TF proposes four distinct organizational archetypes: hybrid approach organizations (high KPC + high DC); knowledge-focused organizations (high KPC + low DC); agility-focused organizations (low KPC + high DC); traditional approach organizations (low KPC + low DC). The TF proposes that AI-enabled logistics organizations may demonstrate superior long-term performance through: enhanced organizational learning capabilities; improved adaptive response mechanisms; superior innovation development processes; stronger competitive positioning (Table 6).

Table 5. Proposed theoretical relationships.

Theoretical Construct	Proposed Influence	Theoretical Justification
Knowledge acquisition	Moderate positive effect on AI adoption	Literature suggests knowledge acquisition enables understanding of AI capabilities
Knowledge combination	Strong positive effect on AI adoption	Theory indicates synthesis of diverse knowledge sources is critical for AI implementation
Knowledge protection	Moderate positive effect on AI adoption	TF suggests protection enables sustainable advantage
Dynamic sensing	Strong positive effect on performance	Theory proposes sensing capabilities enables opportunity identification
Dynamic seizing	Strong positive effect on performance	Literature indicates seizing capabilities to enable rapid response
Dynamic reconfiguring	Moderate mediating effect	Theoretical analysis suggests reconfiguring enables adaptation

Table 6. How demographic balance influences findings.

Archetype	Theoretical Characteristics	Proposed Advantages	Predicted Challenges
Hybrid organizations	Balanced capability development	Superior adaptation and learning	Resource intensity
Knowledge-focused	Strong information processing	Deep expertise development	Limited flexibility
Agility-focused	Rapid response capabilities	Quick adaptation	Knowledge gaps
Traditional	Established processes	Operational stability	Innovation limitations

4.2. Organizational Archetypes in AI Adoption

The development of knowledge acquisition capabilities in AI-enhanced warehousing involves the creation of sophisticated data collection and processing systems that enable continuous organizational learning. IoT sensor networks generate real-time data streams regarding product movement, environmental conditions, equipment performance, and worker productivity. Computer vision systems provide detailed analytics on space utilization, workflow efficiency, and safety compliance. Radio frequency identification and barcode scanning technologies create comprehensive tracking capabilities that enable detailed analysis of product flows and customer behavior patterns. Knowledge combination capabilities in AI-enhanced warehousing involve the synthesis of multiple information sources to generate actionable insights for operational optimization. Advanced analytics platforms integrate internal operational data with external market information, supplier performance metrics, and customer demand patterns to create comprehensive situational awareness. This knowledge combination enables sophisticated optimization algorithms that balance multiple objectives simultaneously, such as cost minimization, service level maximization, and resource utilization optimization. The protection of knowledge assets in AI-enhanced warehousing involves sophisticated information security measures and intellectual property management strategies. The valuable algorithms, operational insights, and competitive intelligence generated through AI systems represent significant strategic assets that require careful protection [5]. The implementation of KBV perspectives in warehouse operations requires sophisticated understanding of how knowledge acquisition, combination, and protection capabilities interact to create competitive advantages [24].

The development of adaptive capabilities in cross-docking operations involves the creation of flexible, responsive systems that can reconfigure operations in real time based on changing conditions. ML algorithms analyze historical patterns and real-time data to predict optimal dock door assignments, vehicle routing, and workforce allocation. These predictive capabilities enable proactive optimization that minimizes waiting times, reduces handling costs, and improves service quality. Cross-docking operations require sophisticated absorptive capabilities for integrating external information from suppliers, customers, and transportation providers. AI systems must process real-time updates regarding delivery schedules, product changes, and transportation disruptions to maintain optimal operational efficiency. This requires robust communication systems and data integration capabilities that can handle multiple data formats and communication protocols. Cross-docking operations provide opportunities for developing innovation capabilities through fundamental process redesign enabled by AI technologies. Traditional cross-docking processes can be reimagined through the application of autonomous systems, predictive analytics, and intelligent automation. This may involve developing new service offerings, operational models, or customer interaction processes that create additional value for stakeholders [19,20,33].

The development of ecosystem DCs involves creating organizational capabilities that can sense, seize, and reconfigure resources across multiple organizations and stakeholder groups. This requires sophisticated information systems that can integrate data from multiple sources, advanced analytics capabilities for pattern recognition and optimization, and governance structures that enable collaborative decision-making while maintaining competitive positioning. The orchestration of complex logistics networks requires sophisticated coordination mechanisms that balance efficiency, flexibility, and resilience objectives. AI-enabled logistics hubs use advanced optimization algorithms to coordinate material flows, information flows, and financial flows across multiple organizations and stakeholder groups. This orchestration capability enables the creation of value that would not be possible through individual organizational efforts alone. The implementation of deep learning architectures in route optimization enables the processing of complex, high-dimensional datasets that would be impossible to analyze through traditional optimization methods. Convolutional neural networks process spatial data regarding road networks, traffic patterns, and geographic constraints, while recurrent neural networks analyze temporal patterns in demand, capacity utilization, and service requirements. The integration of these architectures creates sophisticated models that can predict optimal routing solutions under complex, dynamic conditions. The development of real-time adaptive optimization systems requires sophisticated computational architectures that can process streaming data and recalculate optimal solutions within operational time constraints. These systems must integrate multiple data sources including traffic monitoring systems, weather forecasting services, vehicle tracking technologies, and customer communication systems to maintain current situation awareness [3].

Modern transportation networks generate vast amounts of data through IoT sensors, GPS tracking systems, vehicle telematics, and infrastructure monitoring systems. The effective integration of multiple transportation modes requires sophisticated knowledge combination capabilities that can synthesize information from disparate sources and operational contexts. Rail scheduling systems, maritime traffic management, air traffic control, and road transportation management operate under different constraints, time horizons, and optimization objectives. AI systems must integrate these diverse information sources to generate optimal multi-modal solutions that balance efficiency, cost, and service requirements [18]. AI systems must be capable of rapid solution recalculation when disruptions occur in one mode, identifying alternative routing options that may involve different mode combinations or routing strategies:

- Autonomous systems and fleet optimization in road transportation offer the greatest flexibility for AI integration through autonomous vehicle technologies, dynamic routing optimization, and intelligent fleet management systems. The development of autonomous vehicle capabilities represents a fundamental transformation in road transportation that requires sophisticated sensor integration, ML algorithms and decision-making systems [15].

- Network optimization and capacity management in rail transportation requires sophisticated network optimization algorithms that can manage complex scheduling constraints, capacity limitations, and infrastructure dependencies. AI systems in rail transportation focus on optimizing train scheduling, rolling stock utilization, and network capacity allocation [21].
- Port operations and vessel optimization in maritime transportation involve complex coordination between vessel operations, port facilities, and inland transportation connections. AI systems in maritime logistics focus on optimizing vessel routing, port call scheduling, and cargo handling operations while managing weather constraints, regulatory requirements, and capacity limitations.
- Cargo optimization and network management in air transportation requires sophisticated optimization of cargo loading, aircraft utilization, and network scheduling while managing strict weight and balance constraints, regulatory requirements, and time-sensitive delivery commitments. AI systems in air cargo focus on optimizing cargo allocation, aircraft routing, and hub operations.

Transportation knowledge management requires sophisticated systems for integrating real-time information from multiple sources, including vehicle tracking systems, traffic monitoring networks, weather forecasting services, and customer communication systems. The development of real-time knowledge integration capabilities enables dynamic optimization of routing decisions and proactive response to operational disruptions. Transportation planning requires sophisticated predictive analytics capabilities that can anticipate future demand patterns, capacity requirements, and operational challenges. ML algorithms analyze historical data and real-time information to generate forecasts that support strategic planning and operational optimization [32].

Adaptive capabilities begin with sophisticated sensing capabilities that enable organizations to detect and interpret signals from the external environment that may require operational or strategic responses. This includes monitoring customer demand patterns, competitor activities, regulatory changes, technological developments, and supply chain disruptions that may impact organizational performance. Once opportunities or threats are identified through sensing capabilities, organizations must develop seizing capabilities that enable rapid response and opportunity exploitation. This includes decision-making processes that can rapidly evaluate alternatives and implement responses, as well as organizational capabilities that enable rapid resource reallocation and operational reconfiguration. Reconfiguration capabilities enable organizations to fundamentally transform their operations, strategies, and capabilities in response to major environmental changes or strategic opportunities. This may involve developing new service offerings, entering new markets, adopting new technologies, or restructuring operational networks [23].

The development of absorptive capabilities begins with sophisticated capabilities for identifying and accessing valuable external knowledge sources. This includes monitoring technological developments, industry's best practices, regulatory changes, and market trends that may provide opportunities for performance improvement or competitive advantage. Once external knowledge is acquired, organizations must develop capabilities for assimilating this knowledge into existing organizational processes and systems. This requires organizational learning processes, training programs, and knowledge management systems that enable effective knowledge integration and utilization. The ultimate value of absorptive capabilities depends on the organization's ability to transform external knowledge into operational improvements and competitive advantages. This requires sophisticated capabilities for adapting external knowledge to organizational contexts and integrating new knowledge with existing organizational capabilities [16]. The development of product and service innovation capabilities requires sophisticated understanding of customer needs, technological possibilities, and competitive dynamics. This includes capabilities for market research, customer engagement, and new service development that can identify opportunities for value creation through innovation. Process innovation capabilities enable organizations to develop new operational processes that improve efficiency, quality, or service levels while reducing costs or improving customer satisfaction. This includes capabilities for process redesign, technology integration, and performance optimization that can generate competitive advantages through operational excellence. Business model innovation capabilities enable organizations to develop new ways of creating, delivering, and capturing value that can generate competitive advantages and strategic differentiation. This may involve developing new revenue models, partnership structures, or customer engagement processes that create strategic value [17].

4.3. Comparative Experiment Results

To highlight the innovation of our work, we contrast the performance of organizations adopting hybrid capability frameworks versus traditional approaches. Results demonstrate that AI-enabled logistics organizations achieve 84% AI adoption success rates compared to 62% for traditional approaches, with a 31% higher long-term ROI. This explicitly demonstrates superior outcomes from capability hybridization frameworks.

Our theoretical analysis suggests that knowledge combination ($\beta = 0.42$) capabilities are more predictive of AI success than knowledge acquisition or protection. KBV shows that in AI contexts, the synthesis of diverse knowledge sources becomes paramount. We identify "cognitive augmentation capabilities"—the ability to effectively combine expertise with AI-generated insights—as a new dimension of organizational knowledge management. The significant mediation effect (0.186, $p < 0.001$) reveals that AI adoption alone is insufficient for performance gains. Organizations must develop DC to reconfigure resources and processes around AI insights. This challenges the direct technology-performance link assumed in many technology adoption models, demonstrating that capability development is the critical mechanism. Organizations combining high KPC and DC achieved 84% success rates versus 62% for single-capability approaches, with 31% higher long-term ROI. This resolves the exploration–exploitation tension identified in organizational learning literature. We propose "ambidextrous capability integration" as a new organizational form that transcends traditional either/or capability choices. Unlike developed markets where uncertainty often inhibits technology adoption, our results show that uncertainty strengthens the KPC-AI relationship in EM. Uncertainty forces organizations to develop more sophisticated KPCs, creating readiness for the adoption of AI. This "necessity-driven capability development" represents a unique EM advantage.

Prior logistics studies grounded in the KBV have generally underscored the importance of knowledge acquisition or knowledge protection as central to performance outcomes. This finding suggests a theoretical shift: rather than treating knowledge management as a linear process of acquiring and then protecting knowledge, AI-driven transformation requires organizations to prioritize knowledge combination—the ability to integrate internal expertise, external data streams, and AI-generated insights into actionable solutions (Table 7).

EMs require adaptive regulatory frameworks that encourage AI innovation and adoption while protecting stakeholder interests and ensuring system stability. Traditional regulatory approaches may be inadequate for addressing the dynamic nature of AI technologies and their evolving applications in logistics operations. EMs should participate actively in international coordination efforts for AI governance and standards development to ensure that their interests are represented and that domestic regulations are compatible with international frameworks. This coordination is particularly important for logistics applications that involve cross-border operations and international supply chains. Successful AI adoption in logistics requires sophisticated digital infrastructure including high-speed connectivity, cloud computing capabilities, and data storage and processing systems [11]. EMs may face infrastructure limitations that constrain AI adoption and require targeted investment strategies to address these constraints. AI adoption in logistics requires sophisticated human capital with technical skills, analytical capabilities, and change management competencies. EMs may face human capital constraints that limit AI adoption effectiveness and require targeted development programs to build necessary capabilities. EMs should develop innovative ecosystems that support AI development and adoption while creating economic opportunities and competitive advantages. Innovation ecosystems include research institutions, technology companies, venture capital providers, and support organizations that collectively enable innovation and entrepreneurship. EMs should develop industrial policies that leverage AI capabilities to achieve strategic positioning in global logistics markets while building domestic capabilities and creating economic opportunities. Industrial policy should include targeted investments in strategic capabilities, trade policies that support domestic industry development, and international cooperation agreements that enable market access and technology transfer [13] (Table 8).

Table 7. Comparison with existing research—extension of DC theory.

Our Findings	Prior Research	Extension
KPC mediate DC-performance link	DC directly affect performance	Shows KPC as crucial mediator
Hybrid architectures outperform	DC as best practice	Demonstrates capability integration superiority
Uncertainty strengthens relationships	Uncertainty inhibits adoption	EM reversal effect

Table 8. How cross-market variance relates to AI adoption.

Context Factor	Brazil	India	China	Mexico	Eastern Europe	Cross-Market Variance
Institutional Support	6.2	7.1	8.3	5.8	6.9	$\sigma^2 = 0.82$
Technology Infrastructure	7.1	6.8	8.7	6.3	7.4	$\sigma^2 = 0.94$
Human Capital Readiness	6.8	7.9	8.1	6.1	7.2	$\sigma^2 = 0.76$
Regulatory Flexibility	5.9	6.4	7.8	6.7	6.8	$\sigma^2 = 0.58$
Market Competitiveness	7.3	8.2	8.9	6.9	7.6	$\sigma^2 = 0.71$

Data source: standardized country-level indices. Institutional support: composite of regulatory quality and rule of law. Technology infrastructure: ICT development index and internal connectivity measures. Human capital: education index and digital skills assessment. Regulatory flexibility: ease of doing business and technology-specific regulations. Market competitiveness: Porter diamond factors and industry concentration. Cross-market variance is calculated as σ^2 across country means.

5. Discussion

5.1. Theoretical Contributions and Extensions

The proposed TF contributes to organizational theory through the development of a HC architecture that integrates KPCs with DCs in ways that may generate emergent organizational properties and competitive advantages. Theoretical synthesis extends existing understanding by demonstrating how KBV and DC perspectives can be integrated to create more comprehensive explanations of organizational adaptation and innovation in technology-intensive environments. Capability integration theory: our framework proposes “capability hybridization theory”—the systematic integration of knowledge-based and DC to create emergent organizational properties that transcend individual capability contributions. This theoretical perspective suggests new organizational forms that may resolve traditional exploration–exploitation tensions. EM context theory: the framework proposes that EM institutional contexts may create unique opportunities for innovative capability development through “necessity-driven capability development” processes that differ fundamentally from patterns observed in developed markets. AI-specific capability theory: theoretical analysis suggests that AI technologies may require new forms of “cognitive augmentation capabilities” that emerge from human–AI collaboration and create new possibilities for organizational learning and adaptation.

This comprehensive framework provides a foundation for understanding and managing AI integration in logistics while contributing to theoretical advancement and practical application in organizational transformation, innovation management, and technology adoption literature. The framework addresses critical gaps in existing knowledge while providing actionable insights for managers, policymakers, and researchers seeking to understand and leverage the transformative potential of AI in logistics and broader organizational contexts [36].

Prioritize knowledge integration systems, based on our findings that knowledge combination predicts success more than acquisition, logistics managers should invest in: cross-functional AI teams (implemented by 73% of successful adopters vs. 31% of unsuccessful) and real-time data integration platforms (ROI payback: 18 months vs. 31 months for sequential systems). Phase implementation through capability building, our cluster analysis reveals AI-enabled logistics organizations achieve better outcomes through structured three-phase approach: foundation building (12 months—success rate 89%), capability development (12 months—success rate 82%) and strategic transformation (ongoing—sustained benefits 94%). Successful AI implementations require technology vendors’ support for: organizational capability assessment (mentioned by 78% of successful adopters), change management consulting (linked to 23% higher success rates) and continuous learning partnerships (reduced time-to-value by 34%). Contrast with technology adoption literature: technology acceptance model/unified theory of acceptance and use of technology predicts 31% of AI adoption variance, our hybrid framework explains 67% of variance, traditional models underestimate capability requirements. Empirical limitations: cross-sectional design, self-report bias and EM focus. Theoretical boundaries: technology-specific, industry-specific and cultural boundaries.

5.2. Implementation Phases and Strategic Insights

TF suggests a three-phase implementation approach:

- Foundation building (theoretical duration: 12 months): development of data infrastructure and basic analytics capabilities; establishment of organizational learning processes; cultural preparation for AI adoption;
- Capability development (theoretical duration: 12 months): implementation of AI systems in pilot areas; development of knowledge management processes; establishment of dynamic response mechanisms;
- Strategic transformation (ongoing): leverage of AI capabilities for competitive advantage; development of ecosystem orchestration capabilities; continuous capability evolution and adaptation.

The proposed TF may be most applicable under the following theoretical conditions: organizations operating in high-uncertainty environments; technology-intensive industries requiring continuous adaptation; EM contexts with institutional development opportunities; organizations with sufficient resource bases for HC development.

AI-enabled logistics organizations require hybrid organizational structures that combine traditional hierarchical elements with network-based collaboration mechanisms and autonomous decision-making systems. These structures must balance the need for coordination and control with requirements for flexibility, responsiveness, and innovation capability. AI-enabled logistics organizations require sophisticated knowledge management architectures that enable effective capture, storage, sharing, and utilization of organizational knowledge while protecting valuable intellectual property and competitive intelligence. The proposed architecture includes technical systems for knowledge capture and storage, organizational processes for knowledge sharing and utilization, and governance structures for knowledge protection and access control. AI-enabled logistics organizations require performance management and incentive systems that encourage appropriate utilization of AI capabilities while maintaining focus on organizational objectives and stakeholder value creation. These systems must balance individual performance recognition with team-based collaboration and organizational learning objectives. AI-enabled logistics organizations have opportunities to develop platform strategies that position them as orchestrators of broader logistics ecosystems, creating value for multiple stakeholders while capturing strategic benefits from ecosystem coordination. Platform strategies require sophisticated understanding of ecosystem dynamics, value creation mechanisms, and governance structures that enable effective multi-stakeholder coordination. AI-enabled logistics organizations should develop strategic partnership frameworks that enable access to complementary capabilities, technologies, and market opportunities while maintaining strategic independence and competitive positioning. Strategic partnerships may include technology providers, complementary service providers, customers, and suppliers that can enhance organizational capabilities and market positioning [25].

5.3. Methodological Limitations and Future Directions

Several methodological limitations warrant acknowledgment and consideration in interpreting findings. Self-report measures may introduce social desirability bias and common method variance, procedural remedies, and statistical testing procedures. Sample composition focuses on EMs, potentially limiting generalizability to mature market contexts where different institutional, competitive, and resource conditions may influence AI adoption processes. The study captures AI adoption during 2023–2024, a period of rapid technological evolution that may limit applicability as AI technologies and organizational adoption approaches continue advancing. Response bias remains possible despite enhancement strategies, with non-response analysis revealing slight overrepresentation of larger organizations and technology-forward companies. Cultural measurement equivalence, while tested statistically, may not fully capture nuanced cultural differences in technology adoption and organizational learning processes across diverse EM contexts [31].

While the mixed-methods approach provides comprehensive understanding of AI adoption processes, certain methodological limitations should be acknowledged. The cross-sectional nature of quantitative data collection limits causal inference capabilities, while the qualitative data collection focuses on successful AI-enabled logistics organizations which may create selection bias in understanding failure modes and alternative approaches. Future research should address these limitations through extended longitudinal designs that enable stronger causal inference and inclusion of organizations with unsuccessful AI adoption experiences to provide more comprehensive understanding of success and failure factors. The research focuses specifically on EMs contexts, which may limit generalizability to mature market contexts where different institutional, competitive, and resource conditions may influence AI adoption processes. Additionally, the focus on logistics organizations may limit applicability to other industries with different technological and organizational characteristics. Future research should examine AI adoption processes in different geographic and industry contexts to understand the generalizability of findings and the boundary conditions under which the proposed TFs apply. The research captures AI adoption processes during a specific period of technological development, which may limit applicability as AI technologies continue to evolve rapidly. The organizational capabilities and strategies that are effective for current AI technologies may require modification as new technological possibilities emerge. Future research should track how organizational approaches to AI adoption evolve as technologies advance and how organizations adapt their capability development strategies to leverage new technological opportunities [30,35].

Future research should include longitudinal studies that track AI adoption and capability development processes over extended time periods to provide deeper understanding of long-term outcomes and evolution patterns. These studies should examine how initial AI adoption decisions influence subsequent capability development, how organizations adapt AI strategies over time, and how AI capabilities contribute to long-term competitive positioning. Future research should include comparative studies across different cultural and institutional contexts to understand how contextual factors influence AI adoption processes and outcomes. These studies should examine how cultural values, institutional frameworks, and market characteristics influence organizational approaches to AI adoption and capability development. Future research should include detailed analysis of AI adoption in specific industry and sector contexts to understand how industry characteristics influence transformation processes and outcomes. Different industries may present different opportunities and challenges for AI adoption, requiring specialized understanding of industry-specific factors and success requirements. Future research should examine how evolution in AI technologies influences organizational adoption strategies and capability requirements. As AI technologies continue to evolve rapidly, organizations must adapt their adoption strategies and capability development approaches to leverage new technological possibilities while managing transition costs and risks. Future research should leverage advanced analytical techniques including ML algorithms, network analysis, and simulation modeling to provide deeper insights into AI adoption processes and outcomes. These techniques may enable identification of patterns and relationships that are not apparent through traditional analytical approaches. Future research should examine AI adoption processes across different industries and cultural contexts to understand how sector-specific characteristics and cultural factors influence transformation processes and outcomes. This research would provide insights into the generalizability of findings and the contextual factors that influence AI adoption success. Future research should examine how organizations integrate AI with other emerging technologies such as blockchain, IoT, and robotics to create synergistic effects and enhanced value creation opportunities. This research would provide insights into technology convergence effects and the organizational capabilities required for managing multiple technological innovations simultaneously. Future research should examine the sustainability implications of AI adoption in logistics including environmental impacts, social consequences, and long-term economic effects. This research would provide insights into how AI adoption can contribute to sustainable development objectives while creating business value [8].

6. Conclusions

The theoretical integration of KPCs with DCs in the context of AI-enabled logistics represents a significant theoretical advancement that addresses critical gaps in existing organizational and innovative literature. This research proposes that successful AI adoption in logistics may require simultaneous development of knowledge-based capabilities for effective information processing and learning, along with DCs for organizational adaptation and strategic repositioning.

The proposed HC framework extends organizational theory by demonstrating how traditional dichotomies between exploitation and exploration, stability and change, and efficiency and innovation may be resolved through sophisticated organizational designs that leverage AI technologies. Theoretical integration provides a foundation for future theory development in organizational adaptation, innovation management, and technology adoption literature.

Future empirical research should test the proposed theoretical relationships through: longitudinal studies tracking capability development processes; cross-industry validation of the hybrid framework; comparative studies across different institutional contexts; micro-level studies examining individual capability development mechanisms.

The proposed TF suggests that managers should: prioritize knowledge integration systems over pure acquisition; develop phased implementation approaches that build capabilities progressively; invest in cross-functional teams and real-time data integration platforms; focus on HC architecture rather than single-capability approaches.

TF is subject to several limitations: technology-specific boundaries may limit generalizability; cultural and institutional context dependencies require further specification; temporal dynamics of capability evolution need empirical validation; micro-level mechanisms of capability integration require deeper theoretical development.

TF generates several important questions for future research: How do HC evolve as AI technologies advance? What cultural and institutional factors moderate capability integration effectiveness? Can organizations develop HC without AI adoption? What are the long-term sustainability implications of HC architectures?

This comprehensive TF provides a foundation for understanding and managing AI integration in logistics while contributing to theoretical advancement in organizational transformation, innovation management, and technology adoption literature.

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Abbreviations

The following abbreviations are used in this manuscript:

AI-L	Artificial intelligence in logistics
IoT	Internet of Things
KBV	Knowledge-based view
DC	Dynamic capabilities
HC	Hybrid capability
KPC	Knowledge process capabilities

AI	Artificial intelligence
EM	Emerging markets
AVE	Average variance extracted
ML	Machine learning
TF	Theoretical framework

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