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Wipada Sriwichien and Kittipol Wisaeng *

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Understanding AI Adoption in the Logistics and Supply Chain Industry in Thailand: An Integrated TOE–TTF–UTAUT Framework

Wipada Sriwichien [1] and Kittipol Wisaeng [2,*]

[1] Technology and Business Information System Unit, Mahasarakham Business School, Mahasarakham University, Mahasarakham 44150, Thailand

[2] Technology and Business Information System Unit, Mahasarakham Business School, Mahasarakham University, Mahasarakham 44150, Thailand

* Correspondence: kittipol.w@acc.msu.ac.th; Tel.: +66 086393870

Abstract

Artificial intelligence (AI) is rapidly transforming logistics and supply chain management by enhancing operational efficiency, predictive analytics, and decision-making capabilities. Despite increasing digital transformation initiatives, the determinants of AI adoption in emerging logistics ecosystems remain insufficiently understood. (1) This study aims to develop and empirically examine an integrated framework explaining AI adoption by combining the Technology–Organization–Environment (TOE) framework, Task–Technology Fit (TTF) theory, and the Unified Theory of Acceptance and Use of Technology (UTAUT). (2) Using survey data collected from 500 logistics and supply chain professionals in Thailand, covariance-based structural equation modeling (SEM) was employed to validate the measurement model and test the structural relationships among technological, organizational, environmental, operational, and behavioral factors. (3) The findings indicate that technological, organizational, and environmental contexts significantly influence task–technology fit, while task and technology characteristics strengthen operational alignment between AI systems and logistics activities. Furthermore, performance expectancy, effort expectancy, and social influence significantly enhance behavioral intention, which subsequently drives AI adoption, with facilitating conditions also playing an important supporting role. (4) These results demonstrate that AI adoption in logistics organizations operates through a multi-level mechanism in which structural readiness and operational alignment shape behavioral intention prior to technology implementation, providing theoretical insights and practical guidance for accelerating digital transformation in emerging logistics ecosystems.

Keywords: artificial intelligence adoption; behavioral intention; logistics and supply chain; unified theory of acceptance and use of technology (UTAUT); task-technology Fit (TTF); technology-organization-environment (TOE); structural equation modeling (SEM)

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1. Introduction

The global logistics and supply chain industry is experiencing a profound transformation driven by rapid digitalization and the integration of advanced technologies, particularly artificial intelligence (AI). The increasing complexity of global trade networks, volatile demand patterns, and the need for real-time decision-making have encouraged organizations to adopt intelligent technologies to enhance operational efficiency and responsiveness. Recent research highlights that digital transformation has fundamentally reshaped supply chain structures, enabling organizations to shift from traditional linear logistics operations toward data-driven and interconnected supply chain ecosystems [13,42]. AI technologies including predictive analytics, machine learning, and intelligent routing algorithms, and automated warehousing solutions allow enterprises to manage vast volumes of real-time data and generate actionable insights that improve logistics planning and operational coordination. These technologies allow firms to convert operational data into predictive intelligence, supporting proactive rather than reactive decision-making within logistics operations [26]. Through these capabilities, AI can significantly improve demand forecasting accuracy, optimize transportation routes, enhance inventory management, and strengthen supply chain resilience in uncertain environments [16,26,45]. Empirical studies further indicate that AI-enabled logistics systems can enhance operational transparency, coordination efficiency, and responsiveness across multi-tier supply chain networks [6,30]. As a result, AI is now acknowledged as a strategic enabler of digital transformation, in addition to a technological innovation in logistics and supply chain management, supporting organizations in building adaptive, data-driven supply chain ecosystems [34,42].

The adoption of AI in logistics organizations is often unequal and unrealized, despite the significant potential of AI technologies. Many organizations invest heavily in digital infrastructure and advanced analytics platforms; however, integrating AI systems into existing operational processes remains a significant challenge. Several studies suggest that the discrepancy between the potential of technology and its actual implementation is one of the central challenges of digital transformation initiatives in supply chain management [10]. This gap between technological capability and practical implementation suggests that AI adoption cannot be explained solely by the availability of technological resources. Instead, adoption decisions are influenced by a complex interplay of behavioral perceptions, operational task requirements, and organizational readiness. Research on digital transformation consistently emphasizes that successful technology implementation requires not only technological capabilities but also organizational readiness, human competencies, and alignment with operational processes [42,45]. Recent studies on digital transformation emphasize that technology initiatives frequently fail when organizations underestimate the importance of human decision-making processes, operational task alignment, and organizational capabilities required to support technological change [13,41]. Therefore, a comprehensive understanding of AI adoption requires a multi-dimensional analytical perspective that simultaneously considers behavioral, operational, and contextual determinants.

From a behavioral perspective, the Unified Theory of Acceptance and Use of Technology (UTAUT) provides a widely recognized theoretical foundation for explaining technology adoption behavior. UTAUT proposes that individuals' behavioral intention to adopt and use a technology is influenced by several cognitive perceptions, including performance expectancy, effort expectancy, social influence, and facilitating conditions [49,50]. The model has been extensively utilized in studies of digital technology adoption across many industries, including information systems, healthcare technologies, and logistics management [3]. In logistics environments, performance expectancy is the degree to which logistics professionals believe that AI technologies can improve operational performance by enabling more accurate demand forecasting, optimized route planning, improved warehouse efficiency, and enhanced supply chain visibility. Effort expectancy refers to users' perceptions regarding the complexity or ease of implementing and using AI-based systems within existing logistics operations. Empirical studies in digital logistics and supply chain management confirm that these behavioral perceptions significantly influence technology acceptance and adoption decisions among logistics professionals [38,45]. Performance expectancy has been identified as one of the most potent predictors of technology adoption intentions in data-intensive operational environments such as logistics and supply chain management [38]. Although UTAUT effectively explains user acceptance mechanisms, it primarily focuses on individual behavioral perceptions and does not sufficiently address whether technological capabilities align with the operational tasks users must perform in complex logistics systems.

To mitigate this constraint, Task–Technology Fit (TTF) theory offers an operational perspective that elucidates how the congruence between technological capabilities and task demands affects technology use and performance outcomes. According to TTF theory, technologies enhance user performance only when their functionalities correspond closely with the tasks users must execute

[19]. Recent studies applying TTF in digital environments emphasize that technology adoption outcomes are strongly influenced by how well technological features match the operational demands of users' tasks [8]. In logistics and supply chain management, operational activities such as demand forecasting, warehouse coordination, inventory optimization, route scheduling, and transportation monitoring require high levels of data accuracy, speed, and efficient decision-making. AI technologies can support these tasks through advanced analytics, intelligent automation, and real-time optimization algorithms. However, the effectiveness of these technologies depends on how well their capabilities align with the operational requirements of logistics tasks. When technology capabilities closely match operational needs, organizations are more likely to experience improved decision quality, process efficiency, and operational performance [43]. When there is a strong correlation between operational processes and technology features, AI systems can significantly enhance organizational performance. Conversely, when the alignment between technology and task requirements is weak, companies may have difficulty realizing the potential advantages of advanced technologies, leading to underutilization or implementation failure [11,26]. Therefore, TTF theory provides an important conceptual mechanism that links technological capabilities to operational task performance in logistics environments.

While UTAUT and TTF explain behavioral acceptance and operational alignment, they provide only a limited understanding of the broader contextual conditions that influence technology adoption within organizations. The Technology–Organization–Environment (TOE) framework provides a complementary perspective by elucidating how environmental pressures, organizational characteristics, and technological infrastructure influence innovation adoption at the organizational level [48]. The TOE framework has been widely used to examine the implementation of emergent technologies, including artificial intelligence, big data analytics, and cloud computing, across a variety of organizational settings [9,44]. In logistics organizations, technological readiness encompasses digital infrastructure, data management systems, and system compatibility needed to support AI integration. Organizational readiness encompasses leadership commitment, financial resources, organizational culture, and employee technological capabilities that facilitate the adoption of advanced technologies. Environmental factors include competitive pressure, regulatory frameworks, industry digitalization trends, and collaboration within supply chain networks. Together, these contextual factors determine whether organizations possess the structural capacity and strategic motivation to adopt AI technologies as part of their digital transformation initiatives [32,41].

Although UTAUT, TTF, and TOE have been widely applied in technology adoption research, most existing studies examine these frameworks independently. As a result, the complex interactions between behavioral perceptions, task–technology alignment, and organizational context remain insufficiently understood. Recent literature reviews on artificial intelligence adoption in supply chain management emphasize the need for integrated theoretical models that capture behavioral, technological, and organizational dimensions simultaneously [10,30]. Recent systematic reviews of artificial intelligence adoption in supply chain management highlight the need for integrated theoretical frameworks that simultaneously capture these multiple dimensions [8,13]. Without such integration, existing models may oversimplify the mechanisms underlying technology adoption and fail to explain why organizations with similar technological resources demonstrate significantly different adoption outcomes. Therefore, developing an integrated theoretical model that combines behavioral, operational, and contextual perspectives is essential for advancing understanding of AI adoption in logistics systems.

The logistics and supply chain industry in Thailand provides an important empirical context for examining these issues. Logistics plays a vital role in Thailand's national economy, contributing approximately 14.1% of the country's gross domestic product (GDP) and supporting main sectors such as manufacturing, agriculture, and international trade [33]. Recognizing the strategic importance of logistics modernization, the Thai government has introduced several national initiatives designed to promote digital transformation and technological innovation within the logistics sector. Programs such as Thailand 4.0, the Eastern Economic Corridor (EEC), and the Digital Economy Master Plan aim to strengthen Thailand's competitiveness as a regional logistics hub by encouraging the adoption of advanced technologies, including intelligent transportation systems, artificial intelligence, and big data analytics [37]. Recent studies on digital transformation in Thailand's logistics sector indicate that firms are increasingly under pressure to implement digital technologies to enhance operational efficiency and maintain competitiveness within regional supply chain networks [5]. These barriers include constrained financial resources, deficient technology infrastructure, and poor digital competencies within organizations. Studies examining AI adoption among manufacturing SMEs in Thailand further indicate that digital readiness, organizational capabilities, and technological knowledge significantly influence firms' ability to adopt advanced analytics and intelligent technologies [9]. As a result, many organizations continue to rely on manual processes, fragmented information systems, and paper-based documentation, which restrict real-time data visibility and hinder efficient decision-making. These technological and organizational constraints limit firms' ability to fully utilize AI technologies for demand forecasting, supply chain optimization, and risk management [5]. Sector-specific studies also show that the adoption of digital technologies in Thailand's maritime and logistics industries remains in its early stages, as institutional structures, regulatory frameworks, and organizational capabilities continue to shape the pace of technological transformation [27]. Furthermore, structural barriers such as limited digital readiness among small and medium-sized enterprises (SMEs), shortages of skilled digital professionals, and uneven digital infrastructure across regions create additional challenges for AI implementation in the Thai logistics ecosystem [31]. Consequently, understanding how behavioral perceptions, technological alignment, and organizational readiness interact within the Thai logistics context is essential for explaining the adoption of artificial intelligence technologies in this emerging digital economy.

This paper conceptualizes the adoption of AI in logistics, in response to these difficulties and research gaps, as a multi-level transformation process rather than a simple technology-acceptance decision. Specifically, the study proposes and empirically tests an integrated theoretical framework combining the UTAUT, TTF, and TOE models to explain AI adoption in logistics organizations. Within this integrated framework, behavioral perceptions influence adoption intention, task–technology alignment determines operational effectiveness, and contextual readiness shapes the organizational environment that supports technological innovation. Utilizing survey data gathered from logistics and supply chain experts in Thailand and applying covariance-based structural equation modeling (SEM), this study examines the relationships among behavioral perceptions, task–technology fit, organizational readiness, and AI adoption. The results provide empirical insights into how behavioral, operational, and contextual factors interact to shape AI adoption decisions within logistics organizations. This research enhances the existing literature in multiple ways. First, it integrates behavioral, operational, and contextual perspectives by combining the UTAUT, TTF, and TOE frameworks into a unified theoretical model for AI adoption in logistics. Second, it extends task–technology fit theory by examining its mediating role in the interaction between organizational readiness and behavioral perceptions, and in AI adoption outcomes. Third, the study offers empirical evidence from Thailand's logistics sector, providing context-specific insights into the problems and opportunities associated with digital transformation in emerging logistics ecosystems. These findings have significant implications for policymakers, logistics managers, and technology developers seeking to promote effective AI adoption in supply chain operations. Based on the research gaps identified in the introduction, this study aims to achieve the following objectives:

1. To analyze the principal determinants affecting AI adoption in Thailand's logistics and supply chain sector through a comprehensive TOE, TTF, and UTAUT framework.
2. To examine the effects of behavioral perceptions (performance expectancy, effort expectancy, social influence, and facilitating conditions) on behavioral intention to adopt AI technologies in logistics organizations.

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3. To analyze the role of task–technology fit in enhancing operational effectiveness and supporting AI adoption in logistics processes.
4. To evaluate how technological readiness, organizational readiness, and environmental pressure influence AI adoption within logistics firms.
5. To formulate and empirically validate a comprehensive theoretical model elucidating AI deployment within the Thai logistics and supply chain sector through structural equation modeling (SEM).

2. Literature Review

2.1. Artificial Intelligence in Logistics and Supply Chain Management

Artificial intelligence (AI) has emerged as a disruptive technological force, redefining logistics and supply chain management across global sectors. Rapid progress in predictive analytics, machine learning, and intelligent automation has enabled organizations to significantly improve operational efficiency, strengthen decision-making, and enhance the responsiveness of supply chain networks. AI technologies allow logistics firms to analyze large volumes of structured and unstructured data generated from transportation systems, warehouse operations, and demand forecasting platforms. By utilizing these advanced analytical capabilities, organizations can generate predictive insights that improve planning accuracy, reduce operational uncertainty, and optimize logistics network performance [26,45].

Consequently, AI has become an essential component of modern digital supply chains, facilitating the advancement of sophisticated logistics systems that can respond dynamically to changing market conditions. In logistics and supply chain management, AI applications are increasingly integrated into various operational functions such as demand forecasting, intelligent route optimization, warehouse automation, predictive maintenance, and real-time decision support systems. Predictive analytics models that utilize machine learning algorithms enable firms to forecast demand changes more accurately by analyzing historical data, market trends, and real-time operational information. These forecasting capabilities support more efficient inventory planning and reduce the risks associated with demand uncertainty. Similarly, AI-driven routing algorithms allow transportation systems to dynamically optimize delivery routes based on traffic conditions, fuel consumption, and delivery time constraints, thereby reducing logistics costs and improving service reliability. In warehouse environments, robotics and intelligent automation systems, integrated with AI technologies, enhance inventory tracking accuracy, accelerate order fulfillment, and improve overall operational productivity [26].

Through these applications, AI technologies enable logistics organizations to transform traditional supply chain operations into intelligent, data-driven systems that support efficient coordination and real-time operational visibility. The growing complexity of global supply chains has further accelerated the demand for advanced digital technologies capable of managing large-scale data flows and dynamic operational conditions. Modern logistics networks involve multiple interconnected stakeholders, including manufacturers, distributors, transportation providers, and retailers operating across geographically dispersed environments. Coordinating these complex networks requires continuous monitoring of logistics activities, real-time data integration, and rapid decision-making capabilities. AI technologies enable organizations to process massive volumes of operational data efficiently, allowing logistics managers to identify patterns, detect anomalies, and make data-driven decisions that enhance supply chain resilience and responsiveness [16]. For instance, AI-driven predictive models can detect potential supply chain disruptions, enabling firms to implement proactive risk mitigation strategies. Likewise, AI-supported inventory management systems may optimize stock levels across distribution networks, minimizing holding costs while maintaining high service levels. As a result, AI is increasingly recognized as a key driver of supply chain digital transformation and operational innovation.

Despite the substantial potential benefits of AI technologies, adoption in logistics organizations remains uneven across industries and regions. While large multinational logistics companies often have the financial resources and technological capabilities to implement advanced AI systems, many organizations face substantial barriers to adopting AI-driven solutions. These barriers may include limited technological infrastructure, insufficient data integration capabilities, a shortage of skilled personnel to manage AI systems, and uncertainty about the potential return on investment associated with AI adoption [13,41]. Furthermore, the effective deployment of AI technologies necessitates enterprises to reconfigure current operational processes, develop new technological competencies, and adapt organizational cultures to support digital transformation initiatives. Consequently, AI adoption in logistics should not be viewed as a purely technological decision but rather as a complex organizational transformation process involving multiple interacting factors. Existing studies emphasize that the adoption of advanced digital technologies such as AI is influenced by a combination of technological readiness, organizational capabilities, and user acceptance mechanisms. Technological readiness denotes the availability of digital infrastructure, data integration capabilities, and system compatibility essential to enabling AI applications. Organizational capabilities include leadership support, financial investment, employee technological competencies, and strategic commitment to digital transformation. At the same time, user acceptance plays a crucial role in determining whether employees are willing to utilize AI technologies within operational processes. If logistics professionals perceive AI systems as complex, unreliable, or incompatible with their tasks, they may resist adopting these technologies even when organizations invest heavily in digital infrastructure. Therefore, understanding AI adoption requires an integrated theoretical perspective that simultaneously considers technological, organizational, and behavioral determinants of innovation adoption.

Nonetheless, previous studies on AI implementation in logistics and supply chain management have often depended on singular theoretical frameworks, which often produce fragmented and incomplete insights into adoption dynamics. Some studies focus primarily on technological factors influencing the diffusion of innovation, while others emphasize individual behavioral perceptions or organizational readiness conditions. Although these approaches contribute valuable insights, they often fail to capture the complex interactions among behavioral, operational, and contextual factors that shape AI adoption decisions in real-world logistics environments [16,17]. As logistics systems become increasingly digitalized and data-driven, a more comprehensive theoretical framework is required to explain how these multiple dimensions interact to influence technology adoption outcomes.

2.2. Technology-Organization-Environment (TOE): The Structural Context Layer

The Technology–Organization–Environment (TOE) framework is commonly employed to explain the adoption of technological innovations by organizations through the analysis of three contextual dimensions: technological readiness, organizational competence, and environmental pressure [32]. The TOE framework is especially pertinent in logistics and supply chain management because implementing artificial intelligence (AI) requires comprehensive integration across data infrastructures, operational workflows, and inter-organizational networks, rather than isolated technological deployment. Logistics systems involve multiple stakeholders, including transportation providers, warehouses, suppliers, and distributors, which increases the importance of contextual conditions that support technological innovation [25].

In the technological environment, adoption decisions are influenced by factors including system compatibility, technological complexity, and the development of digital infrastructure. Compatibility is the extent to which new technologies can be integrated with existing operational systems, such as facility management platforms or transportation management systems. Complexity may affect the ease of implementation, as highly sophisticated AI technologies often require advanced technical expertise and organizational adjustments. In addition, the availability of digital infrastructure, including data integration capability and system interoperability, plays a crucial role in enabling AI-

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driven logistics operations. Empirical studies indicate that organizations with well-developed digital infrastructures are more likely to adopt emerging technologies because they possess the essential technological foundations for data exchange and system integration [22,25]. However, concerns related to technological complexity and data security may limit adoption, particularly in organizations operating within heterogeneous digital environments [32].

The organizational context emphasizes internal resources and capabilities that enable firms to implement technological innovations. Key organizational factors include leadership support, financial investment, IT capability, and innovation-oriented culture. Strong managerial commitment and adequate financial resources are essential to support digital transformation initiatives and facilitate AI implementation. Similarly, organizations with higher levels of technological expertise and digital capability are better positioned to integrate advanced technologies into their operational processes [1,41].

In the context of the environment, external pressures include competitive intensity, regulatory support, and industry digitalization trends. In emerging economies, government policies and competitive pressure often accelerate technology adoption by encouraging firms to modernize their operational systems [44,53]. Although TOE explains structural readiness, it does not clarify how contextual factors translate into operational effectiveness, suggesting the need to incorporate additional perspectives, such as Task–Technology Fit, to explain technology utilization in logistics tasks.

2.3. Task-Technology Fit (TTF): The Operational Transmission Mechanism

While the TechnologyOrganization–Environment (TOE) framework explains whether organizations possess the structural readiness to incorporate emerging technologies, including artificial intelligence (AI), structural preparedness alone does not guarantee successful implementation. Organizations may have advanced digital infrastructure, strong managerial support, and favorable environmental conditions; however, AI systems often remain underutilized or disconnected from daily operations. This gap between technological availability and practical utilization indicates that adoption effectiveness depends not only on contextual readiness but also on the degree to which technological capabilities align with operational task requirements. Task–Technology Fit (TTF) theory provides a mechanism for explaining how structural readiness translates into operational viability and performance outcomes. TTF theory proposes that technology improves user performance only when its functionalities effectively support the execution requirements of specific tasks [19].

In logistics and supply chain management environments, operational tasks are typically characterized by high complexity, temporal sensitivity, uncertainty, and interorganizational coordination. Activities such as demand forecasting, route planning, inventory allocation, warehouse coordination, and disruption management require the ability to make rapid decisions and access accurate information in a timely manner. AI technologies have the potential to enhance these logistics tasks by providing advanced analytical capabilities and real-time operational insights. However, the effectiveness of these technologies depends on whether their functionalities align with the operational logic of logistics processes [11,26]. When task–technology alignment is weak, a structural bottleneck can emerge even when technological infrastructure and organizational support are present. AI systems that produce outputs that cannot be easily integrated into existing workflows may increase users' cognitive burden and create resistance to using the technology. In such cases, employees may perceive AI technologies as complex or impractical, leading to limited adoption and reduced operational impact. Empirical studies in digital logistics environments demonstrate that investments in advanced analytics and AI systems do not automatically lead to improved operational performance unless technological capabilities are synchronized with the requirements of operational workflows [25,41].

Therefore, TTF represents an essential conversion stage in the technology adoption process, determining whether structural readiness described by the TOE framework can be translated into actionable operational capability. From a cross-level perspective, contextual enablers such as technological compatibility, digital infrastructure, and organizational support facilitate configuring AI systems to align with operational task requirements. When this alignment is achieved, AI technologies can reduce operational uncertainty, accelerate decision cycles, and improve coordination across supply chain processes. Such alignment also strengthens users' perceptions of technology's usefulness, as employees can directly observe how AI systems enhance their daily tasks. Conversely, when task–technology fit is weak, users may struggle to recognize the practical benefits of AI technologies, reducing their perceived usefulness and increasing resistance to adoption.

Within the integrated TOE–TTF–UTAUT framework proposed in this study, task–technology fit functions as both a mediating and enabling mechanism. First, TTF mediates the relationship between structural readiness and user perceptions by translating technological and organizational conditions into operationally relevant capabilities. Second, it amplifies the influence of behavioral determinants such as performance expectancy on adoption intention. When AI technologies demonstrate clear alignment with logistics tasks, users are more likely to perceive them as beneficial and practical for improving operational performance. Ultimately, the performance benefits of AI adoption in logistics can be realized only when AI systems are effectively embedded in operational workflows. In this regard, TTF functions as a vital operational transfer mechanism that determines whether investments in AI technologies generate tangible organizational value or remain symbolic technological initiatives [11]. Therefore, within the proposed integrated framework, task–technology fit serves as the meso-level alignment layer that links macro-level contextual readiness to micro-level behavioral acceptance, thereby enabling sustainable AI implementation and performance improvement in logistics and supply chain systems.

2.4. Unified Theory of Acceptance and Use of Technology (UTAUT): The Behavioral Activation Engine

While the Technology–Organization–Environment (TOE) framework explains the structural feasibility of adopting artificial intelligence (AI) and Task–Technology Fit (TTF) determines whether technological capabilities align with operational requirements, the Unified Theory of Acceptance and Use of Technology (UTAUT) explains whether these technologies become behaviorally activated within organizations. Developed by [49] and later extended in subsequent research, UTAUT conceptualizes technology adoption as a function of four primary determinants: performance expectancy, effort expectancy, social influence, and facilitating conditions.

Nevertheless, these determinants do not function autonomously in the context of AI-driven logistics transformation. Instead, they function as behavioral mechanisms influenced by the structural readiness and operational alignment established by preceding layers of the adoption framework. Performance expectancy is the extent to which individuals anticipate that implementing a specific technology will improve their job performance. In logistics and supply chain operations, performance expectancy is associated with perceived improvements in operational efficiency, including more accurate demand forecasting, optimized transportation routing, improved inventory visibility, and faster responses to supply chain disruptions. Prior studies in digital supply chain management consistently identify that performance expectancy is the most influential predictor of technology adoption intention, as users are more likely to adopt technologies that obviously enhance their productivity and decision-making capabilities [16,52]

However, perceptions of performance improvement are often shaped by users' experiences with the technology in real operational contexts. When AI systems demonstrate clear alignment with logistics tasks, users can directly observe improvements in their work processes, strengthening perceived usefulness and encouraging adoption. Conversely, when task–technology alignment is weak, expected performance benefits may remain abstract and insufficient to motivate sustained adoption behavior. Effort expectancy reflects the perceived simplicity or difficulty of utilizing a technology. In logistics environments, where operational processes are time-sensitive and require constant coordination among multiple actors, technologies that are perceived as complex or difficult to use may discourage adoption. High levels of perceived complexity can increase cognitive workload and create resistance among employees responsible for managing logistics processes [45].

Nevertheless, effort expectancy is also influenced by operational alignment. When AI technologies integrate seamlessly into existing workflows, users perceive them as easier to use and less disruptive to their daily tasks. In contrast, poor task–technology alignment can increase perceived effort and reduce acceptance, even when organizations possess sufficient technological infrastructure and support. Social influence refers to individuals' belief that a significant stakeholder is impacting the adoption of a specific technology. As logistics ecosystems rapidly digitalize, normative pressure from management, industry trends, and government initiatives can motivate organizations to experiment with AI-based technologies [53].

However, while social influence can stimulate initial interest or experimentation, long-term adoption typically depends on whether users experience tangible performance benefits from using the technology. Facilitating conditions refer to the presence of organizational and technical support that enables technology utilization, including training programs, IT infrastructure, and technical assistance. Empirical studies indicate that facilitating conditions play a key role in reducing implementation barriers and supporting the transition from adoption intention to actual technology usage [41].

Within the integrated TOE–TTF–UTAUT framework proposed in this study, facilitating conditions strengthen the implementation process by reducing uncertainty and ensuring employees have the necessary resources to use AI technologies effectively. From a cross-level perspective, UTAUT functions as the final behavioral activation layer within the sequential adoption process. Structural readiness, described by the TOE framework, enables the development of technological capabilities, while TTF ensures that these capabilities align with operational task requirements. These factors subsequently shape users' cognitive evaluations of AI technologies, including perceived usefulness and ease of use. These cognitive perceptions generate behavioral intention, which ultimately drives AI adoption and utilization within logistics organizations. When behavioral intention is supported by strong structural readiness and effective task–technology alignment, AI adoption can lead to measurable improvements in supply chain performance, including enhanced efficiency, responsiveness, and resilience [51,52]. Therefore, within this study's integrated TOE–TTF–UTAUT framework, UTAUT functions not merely as a standalone acceptance model but as a behavioral activation mechanism that converts operational viability into sustained technology implementation. AI adoption emerges from a multi-level process in which contextual readiness supports operational alignment, operational alignment shapes cognitive evaluation, and cognitive evaluation ultimately drives behavioral adoption and performance realization in logistics and supply chain systems.

3. Integrated Conceptual Model and Hypothesis Development

The rapid digital transformation of logistics and supply chain management has intensified academic interest in understanding the mechanisms underlying the adoption of artificial intelligence (AI) within organizational environments. Recent systematic reviews and bibliometric analyses indicate that AI adoption in supply chains is not determined solely by technological availability but by the alignment of multiple determinants, including technological capabilities, organizational readiness, environmental pressures, operational task characteristics, and user-level acceptance dynamics [8,13]. As supply chain systems become increasingly complex and data-driven, organizations must simultaneously manage structural readiness, operational alignment, and behavioral acceptance in order to successfully implement AI-enabled technologies. Although previous studies have examined the Technology–Organization–Environment (TOE), Task–Technology Fit (TTF), and Unified Theory of Acceptance and Use of Technology (UTAUT) frameworks independently, emerging research suggests that a single-theory perspective is insufficient for explaining complex digital transformation processes. Instead, scholars increasingly advocate the use of integrated, multilevel models that simultaneously capture structural, operational,

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and behavioral determinants of technology adoption [4,29]. Drawing upon these perspectives, this study proposes an integrated TOE–TTF–UTAUT framework to explain AI adoption in Thailand's logistics and supply chain industry. Within this framework, determinants operate across three analytical levels: structural factors explained by the TOE framework, operational alignment captured by TTF theory, and behavioral acceptance mechanisms explained by UTAUT.

3.1. Structural Level: TOE as Enabling Conditions (H1-H3)

At the structural level, the Technology–Organization–Environment framework explains how organizational contexts influence the adoption of innovation. The TOE framework suggests that technological attributes, organizational capabilities, and environmental pressures collectively shape organizations' readiness to adopt new technologies. Within the technological context (TEC), AI adoption is influenced by several key attributes, including perceived complexity, compatibility with existing systems, availability of AI technologies, and relative advantage. High technological complexity may increase implementation uncertainty and operational risk, thereby discouraging adoption. In contrast, compatibility between AI systems and existing technological infrastructure facilitates integration and reduces barriers to transition. The availability of AI technologies and the perceived relative advantage associated with their use further strengthen adoption decisions by highlighting potential performance benefits. Prior studies demonstrate that these technological attributes significantly influence the adoption of emerging digital technologies in logistics and supply chain environments [12,36]. Accordingly, technological factors are expected to directly influence AI adoption in logistics organizations.

H1. *Technological factors significantly influence AI adoption in logistics and supply chain management.*

H1a. *Perceived complexity of AI negatively influences AI adoption.*

H1b. *Compatibility of AI positively influences AI adoption.*

H1c. *Availability of AI technology positively influences AI adoption.*

H1d. *Perceived relative advantage of AI positively influences AI adoption.*

Within the organizational context (ORG), AI adoption is shaped by internal governance structures and organizational resources. Top management support plays a crucial role in reducing strategic uncertainty and signaling organizational commitment to digital transformation initiatives. Firm size may also influence adoption decisions, as larger organizations often possess greater financial resources and higher risk tolerance. Additionally, organizational readiness facilitates the implementation of AI technologies. Technical capabilities among employees further support the sustainability of technology adoption by enabling organizations to manage and operate AI systems effectively. Empirical studies emphasize that managerial commitment and organizational resources are critical factors influencing the adoption of digital innovation [4]. Therefore, organizational factors are expected to directly influence AI adoption in logistics firms.

H2. *Organizational factors significantly influence AI adoption in logistics and supply chain management.*

H2a. *Top management support positively influences AI adoption.*

H2b. *Larger firm size positively influences AI adoption.*

H2c. *Organizational readiness positively influences AI adoption.*

H2d. *Technical capabilities positively influence AI adoption.*

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At the environmental level (ENV), external institutional forces influence organizations' incentives to adopt new technologies. Regulatory policies and government initiatives can encourage digital transformation by reducing legal uncertainties and promoting technological innovation. Similarly, customer pressure for improved logistics services and supply chain transparency may motivate organizations to adopt advanced technologies such as AI. Competitive dynamics within the logistics industry further increase the need for efficiency and innovation, encouraging firms to adopt technologies that enhance operational performance and strategic differentiation [2,37]. Therefore, environmental factors are expected to exert a direct influence on AI adoption.

H3. *Environmental factors significantly influence AI adoption in logistics and supply chain management.*

H3a. *Regulatory environment positively influences AI adoption.*

H3b. *Customer pressure positively influences AI adoption.*

H3c. *Competitive dynamics positively influence AI adoption.*

3.2. Operational Level: TTF as Alignment Mechanism (H4-H7)

Although the TOE framework explains structural readiness for innovation adoption, it does not explicitly address whether technological capabilities align effectively with operational task requirements. Task–Technology Fit (TTF) theory addresses this limitation by emphasizing that technology improves performance only when its capabilities correspond closely with the characteristics of the tasks it is intended to support. In logistics and supply chain management, operational tasks such as transportation planning, demand forecasting, inventory management, and disruption mitigation require high levels of coordination and data processing. AI technologies can significantly improve operational performance when they are properly aligned with these task requirements. Recent research on AI-enabled supply chains confirms that intelligent systems generate measurable improvements in efficiency, sustainability, and cost reduction only when their technological capabilities align with operational tasks [7]. Bibliometric analyses further highlight the growing importance of aligning AI technologies with the complexity of logistics tasks to maximize performance benefits [8]. Empirical studies applying TTF theory in digital environments demonstrate that task characteristics (TAS) and technology characteristics (TCH) jointly influence the perceived level of task–technology fit. When the characteristics of AI systems match the requirements of logistics tasks, users are more likely to perceive the technology as useful and beneficial for improving operational performance [43]. Accordingly, this study proposes the following hypotheses:

H4. *Task characteristics positively influence task-technology fit.*

H5. *Technology characteristics positively influence task-technology fit.*

H6. *Task-technology fit positively influences performance expectancy.*

H7. *Task-technology fit positively influences AI adoption.*

Within the integrated framework, TTF functions as an operational bridge, linking structural readiness, as explained by the TOE framework, with user-level cognitive evaluations described in the UTAUT model.

3.3. Behavioral Level: UTAUT as Acceptance Mechanism (H8-H12)

At the behavioral level, the Unified Theory of Acceptance and Use of Technology explains how individual perceptions influence technology adoption decisions. According to UTAUT, behavioral intention to adopt technology is primarily influenced by performance expectancy, effort expectancy, social influence, and facilitating conditions. In AI-enabled logistics environments, performance expectancy (PE) reflects users' perceptions that AI technologies can improve operational efficiency and decision-making quality. Effort expectancy (EE) refers to the perceived ease of using AI systems within logistics operations. Social influence (SI) captures the extent to which individuals perceive that key stakeholders encourage the use of AI technologies, whereas facilitating conditions (FC) reflect the availability of technical infrastructure, training, and organizational support required to implement AI systems. Empirical studies in logistics and digital transformation contexts confirm that these factors significantly influence behavioral intention and technology adoption outcomes [3,29,38].

Behavioral intention (BI) is further expected to mediate the relationship between cognitive perceptions and actual AI adoption behavior. Therefore, the following hypotheses are proposed:

H8. *Performance expectancy positively influences behavioral intention.*

H9. *Effort expectancy positively influences behavioral intention.*

H10. *Social influence positively influences behavioral intention.*

H11. *Facilitating conditions positively influence AI adoption.*

H12. *Behavioral intention positively influences AI adoption.*

3.4. Integrated Multilevel Logic

The integrated TOE–TTF–UTAUT model conceptualizes AI adoption as a sequential, multi-level process in which structural conditions, operational alignment, and behavioral mechanisms interact to shape implementation outcomes. At the structural level, the TOE framework explains how technological readiness, organizational capabilities, and environmental pressures establish the foundational feasibility of AI deployment within logistics firms. These contextual factors determine whether organizations possess the resources, leadership commitment, and institutional incentives necessary to initiate digital transformation initiatives. At the operational level, Task–Technology Fit ensures that AI capabilities align with the requirements of logistics tasks, thereby improving system effectiveness and strengthening perceptions of technological usefulness. Finally, at the behavioral level, the UTAUT framework explains how users' cognitive evaluations influence behavioral intention and actual AI usage. This layered and interconnected mechanism reflects recent scholarly calls for integrated frameworks that simultaneously explain technology adoption from structural, operational, and behavioral perspectives [4,13]. The complete conceptual framework and the hypothesized relationships (H1–H12) proposed in this study are illustrated in Figure 1.

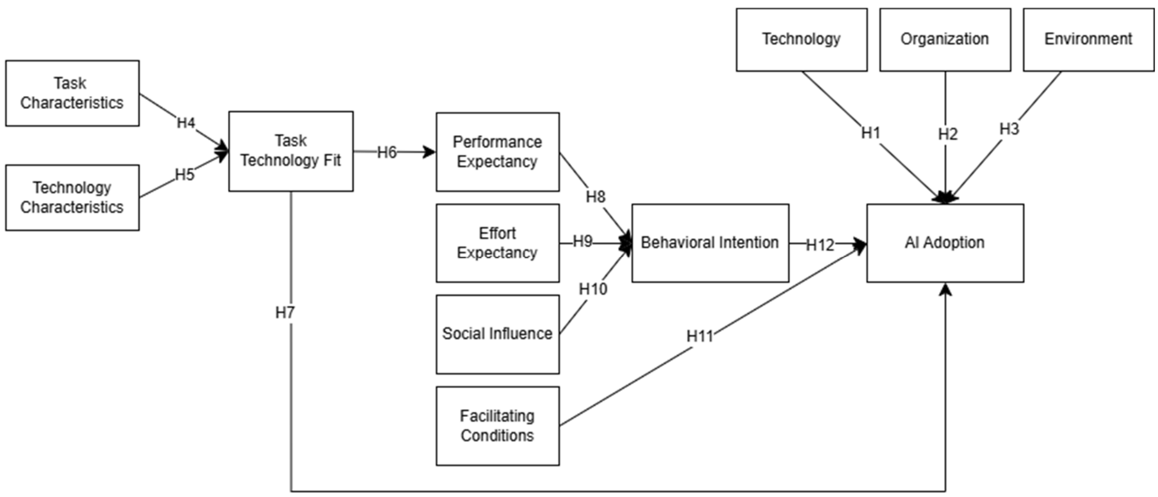

Figure 1. Conceptual Model.

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The integrated conceptual framework developed in this study explains the adoption of artificial intelligence (AI) in logistics and supply chain management. The framework combines the Technology–Organization–Environment (TOE), Task–Technology Fit (TTF), and Unified Theory of Acceptance and Use of Technology (UTAUT) perspectives. As shown in Table 1, structural factors derived from the TOE framework establish the contextual readiness for AI adoption, encompassing technological, organizational, and environmental conditions. At the operational level, task and technology characteristics determine task–technology fit, which enhances perceptions of performance. At the behavioral level, UTAUT constructs influence behavioral intention and actual AI adoption. Together, these levels explain the multilevel process of AI adoption in logistics organizations.

Table 1. Summary of the Integrated TOE–TTF–UTAUT Conceptual Model for AI Adoption in Logistics and Supply Chain Management.

Level	Theory	Construct	Description	Hypothesis
Structural Level	TOE	Technological Context (TEC)	Technological attributes that determine AI feasibility, including complexity, compatibility, availability, and the relative advantage of AI technologies.	H1
		Perceived Complexity	The degree to which AI technologies are perceived as difficult to understand or implement.	H1a
		Compatibility	The extent to which AI technologies align with existing systems and operational processes.	H1b
		Availability of AI Technology	The accessibility and maturity of AI infrastructure and tools within logistics organizations.	H1c
		Relative Advantage	The perceived performance improvement gained from adopting AI technologies.	H1d
	TOE	Organizational Context (ORG)	Internal organizational capabilities and resources influencing AI adoption decisions.	H2
		Top Management Support	The commitment of senior leadership to promote AI adoption and digital transformation.	H2a
		Firm Size	The scale of organizational resources and risk absorption capacity.	H2b
		Organizational Readiness	The preparedness of organizational infrastructure and change management capability for AI implementation.	H2c
		Technical Capabilities	The availability of skilled personnel and technological expertise to manage AI systems.	H2d
	TOE	Environmental Context (ENV)	External pressures influencing technology adoption in logistics ecosystems.	H3

		Regulatory Environment	Government policies and institutional support promote digital transformation.	H3a
		Customer Pressure	Demand from customers for advanced technological services and logistics transparency.	H3b
		Competitive Dynamics	Competitive intensity is encouraging firms to adopt AI technologies to gain a strategic advantage.	H3c
Operational Level	TTF	Task Characteristics (TAS)	The complexity, interdependence, and analytical requirements of logistics operations.	H4
		Technology Characteristics (TCH)	Functional capabilities of AI technologies, such as predictive analytics and automation.	H5
		Task–Technology Fit (TTF)	The degree to which AI technologies align with logistics task requirements.	H6, H7
Behavioral Level	UTAUT	Performance Expectancy (PE)	The extent to which users believe AI improves operational performance.	H8
		Effort Expectancy (EE)	The perceived ease of using AI technologies in logistics tasks.	H9
		Social Influence (SI)	The degree to which important stakeholders encourage AI adoption.	H10
		Facilitating Conditions (FC)	The availability of organizational and technological support for AI implementation.	H11
		Behavioral Intention (BI)	The intention of users to adopt AI technologies in logistics operations.	H12
Outcome	Integrated Model	AI Adoption (AI)	The actual implementation and use of AI technologies in logistics and supply chain management.	—

3.5. Research Gap

Although artificial intelligence has attracted increasing scholarly attention in logistics and supply chain management, several critical research gaps remain in the existing literature. First, many previous studies have primarily examined AI adoption from a single theoretical perspective, focusing on either technological readiness (TOE), operational alignment (TTF), or user acceptance behavior (UTAUT). While these frameworks provide valuable insights into specific aspects of technology adoption, they often fail to capture the complex interactions among structural, operational, and behavioral determinants that influence AI implementation in real-world logistics environments [8,13]. Recent reviews of artificial intelligence adoption in supply chain management indicate that existing studies often analyze technological, organizational, and behavioral dimensions separately, resulting in fragmented theoretical explanations of digital transformation processes [13]. As a result, existing studies provide fragmented explanations of AI adoption processes.

Second, prior research frequently emphasizes technological availability and infrastructure readiness as primary determinants of AI adoption. However, evidence suggests that the mere presence of advanced digital technologies does not guarantee successful implementation. Organizations may possess adequate technological resources yet still struggle to realize operational benefits due to misalignment between technological capabilities and logistics task requirements. Recent empirical studies emphasize that the effectiveness of AI technologies depends strongly on how well technological capabilities align with operational tasks and decision-making processes within supply chain systems [8]. This limitation highlights the need to incorporate operational perspectives, particularly task–technology fit, to explain how technological systems interact with logistics workflows and decision-making processes.

Third, most empirical studies on AI adoption in supply chain management have been conducted in developed economies, such as the United States, Europe, and China. Consequently, there is limited empirical evidence regarding AI adoption mechanisms in emerging economies where digital infrastructure maturity, institutional environments, and organizational capabilities differ significantly. Scholars increasingly emphasize the importance of investigating technology adoption within emerging economies, where organizational resources, institutional environments, and technological capabilities differ substantially from those in developed countries [42]. In particular, research focusing on the logistics and supply chain industry in Thailand remains scarce, despite the sector's strategic importance to national economic development and digital transformation initiatives.

Fourth, previous studies rarely examine AI adoption as a multi-level transformation process that simultaneously integrates structural conditions, operational alignment, and behavioral acceptance. Without such an integrative perspective, existing models cannot adequately explain how contextual readiness influences task-level technology alignment and, in turn, shapes user perceptions and adoption behavior. Recent literature reviews highlight the need for integrated theoretical models that simultaneously incorporate behavioral acceptance mechanisms, operational task alignment, and organizational readiness in order to better explain AI adoption in complex supply chain environments [13,45].

To address these limitations, this study formulates a comprehensive TOE–TTF–UTAUT framework to investigate AI adoption within Thailand's logistics and supply chain sector. This study integrates structural, operational, and behavioral perspectives into a cohesive conceptual model, thereby delivering a more thorough elucidation of AI adoption mechanisms and providing empirical insights into the progression of digital transformation within logistics organizations in emerging economies. This integrated approach enhances existing research on how technical preparedness, task-technology alignment, and behavioral perspectives affect the adoption of artificial intelligence in supply chain systems [11,42].

4. Research Methodology

4.1. Research Design

This study adopts a quantitative research design to investigate the determinants of artificial intelligence (AI) adoption in Thailand's logistics and supply chain industry. The proposed conceptual framework examines relationships among multiple latent constructs derived from the integrated Technology–Organization–Environment (TOE), Task–Technology Fit (TTF), and Unified Theory of Acceptance and Use of Technology (UTAUT) models. These constructs represent key theoretical concepts including technological readiness, organizational capability, environmental pressure, task–technology alignment, and behavioral intention. Quantitative methods enable the systematic measurement of these constructs and facilitate hypothesis testing through statistical analysis. Recent studies on digital transformation and technology adoption in logistics and supply chain contexts frequently employ quantitative survey approaches to empirically examine relationships among technological, organizational, and behavioral determinants of innovation adoption [42,45]. This research employs a cross-sectional survey design, collecting data from logistics and supply chain professionals at a single point in time. Cross-sectional surveys are widely used in technology adoption research because they capture current perceptions, organizational readiness, and technological conditions influencing adoption decisions. Such designs are particularly well-suited to examining the relationships among user perceptions, organizational factors, and innovation adoption within a specific temporal context [13]. To analyze the proposed conceptual model, this study applies Structural Equation Modeling (SEM). SEM enables the simultaneous evaluation of measurement models and structural relationships among latent variables and is particularly suitable for testing complex theoretical frameworks involving multiple constructs. Recent empirical studies examining digital technology and AI adoption in supply chain systems increasingly use SEM because of its ability to assess measurement validity and theoretical relationships among constructs [11,26]. In this study, SEM is used to evaluate measurement reliability and validity through confirmatory factor analysis (CFA) and to test the hypothesized relationships within the integrated TOE–TTF–UTAUT framework. Data are collected through a structured questionnaire administered to professionals working in logistics and supply chain organizations in Thailand, including managers, operations supervisors, and IT specialists knowledgeable in digital technologies and logistics operations. Survey-based data collection from industry practitioners is widely used in logistics research because respondents possess direct insights into operational processes, technological implementation, and organizational decision-making related to digital transformation initiatives [5,9]

4.2. Sample and Data Collection

Data for this study were collected from logistics and supply chain professionals in Thailand using purposive sampling. Respondents were selected based on their professional involvement in logistics operations, supply chain management, or digital transformation initiatives within their organizations. This selection criterion ensured that participants possessed relevant knowledge and practical experience in the adoption of artificial intelligence (AI) in logistics and supply chain activities. The data collection process was conducted over a one-month period, from 5 February to 4 March 2026. To determine an appropriate sample size for Structural Equation Modeling (SEM) analysis, this study followed the guidelines proposed by [20], which recommend a minimum of 10 respondents per observed variable. Since the research model includes 20 observed variables, the minimum required sample size was 200 respondents. In total, 500 valid responses were collected and retained for analysis. This sample size exceeds the recommended threshold for SEM analysis and provides sufficient statistical power for reliable hypothesis testing.

4.3. Measurement Development

The measurement instruments used in this study were developed from established scales in prior research related to the Technology–Organization–Environment (TOE), Task–Technology Fit (TTF), and Unified Theory of Acceptance and Use of Technology (UTAUT) frameworks. Adapting validated measurement items helps ensure theoretical consistency and enhances the content validity of the research instrument. Previous studies on digital transformation and technology adoption in logistics and supply chain contexts commonly apply validated measurement scales derived from established theoretical frameworks to ensure conceptual rigor and measurement reliability [42,45]. Each construct in the conceptual model was measured using multiple items to capture different dimensions of the underlying theoretical concepts. The use of multi-item measurement scales is recommended in structural equation modeling research because it improves construct reliability and enables more accurate estimation of latent variables [21,23]. All measurement items were evaluated using a five-point Likert scale ranging from 1 ("strongly disagree") to 5 ("strongly agree"), which is widely used in technology adoption and organizational behavior research. Likert-type scales enable the consistent measurement of subjective perceptions and behavioral intentions in survey-based studies [30]. Before the main survey was conducted, a pilot test involving 30 logistics and supply chain professionals was conducted to evaluate the questionnaire's clarity, reliability, and overall consistency. Pilot testing is widely recommended in survey research to identify potential measurement errors and improve instrument validity prior to large-scale data collection [21]. Based

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on pilot test feedback, minor revisions were made to improve the clarity of several measurement items. To reduce the risk of common method bias (CMB), several procedural remedies were applied during questionnaire design and data collection. Respondent anonymity was guaranteed to reduce evaluation apprehension, and measurement items for different constructs were separated to minimize response pattern bias. These procedural remedies are commonly recommended in survey-based behavioral research to reduce potential bias associated with self-reported data [18,39]. Common method bias was further assessed using Harman's single-factor test through unrotated principal component analysis. The first factor explained 30.53% of the total variance, which is below the recommended 50% threshold. According to methodological guidelines, when a single factor does not account for the majority of variance, common method bias is unlikely to substantially affect the results [21,39]. These results suggest that common method bias is not a serious concern in this study.

4.4. Data Analysis Strategy

The data analysis in this study followed a two-step Structural Equation Modeling (SEM) procedure commonly recommended for evaluating complex theoretical models involving multiple latent constructs. The two-step SEM approach consists of assessing the measurement model before evaluating the structural model, ensuring the reliability and validity of latent constructs prior to hypothesis testing [21,30]. In the first step, Confirmatory Factor Analysis (CFA) was conducted to evaluate the reliability and validity of the measurement model and to verify whether the observed variables adequately represent their underlying constructs. Internal consistency reliability was assessed using Composite Reliability (CR), which is widely recommended in SEM research for evaluating construct reliability [21]. Convergent validity was evaluated using standardized factor loadings and Average Variance Extracted (AVE). Factor loadings greater than 0.70 and AVE values above 0.50 indicate satisfactory convergent validity of measurement items [17,21]. Discriminant validity was also examined to ensure that each construct is empirically distinct from other constructs within the model, following established SEM guidelines [23]. In the second step, the structural model was estimated to test the hypothesized relationships among constructs in the integrated TOE–TTF–UTAUT framework. SEM enables the simultaneous estimation of multiple relationships among latent variables and is widely used for testing complex theoretical models [21,30]. Model fit was evaluated using several goodness-of-fit indices, including chi-square/degrees of freedom (χ^2/df), Root Mean Square Error of Approximation (RMSEA), Comparative Fit Index (CFI), and Tucker–Lewis Index (TLI). These indices are commonly used to assess the adequacy of SEM models in representing the observed data [21,30]. The results indicated that the model fit satisfactorily according to established SEM thresholds.

4.5. Ethical Approval and Pilot Testing

Ethical approval for this study was obtained from the Mahasarakham University Ethics Committee for Research Involving Human Subjects (Approval No. 092-874/2026) prior to the commencement of data collection. The research was conducted in accordance with established ethical guidelines to ensure the protection of participants' rights and confidentiality. Before completing the questionnaire, all respondents were provided with detailed information regarding the study's objectives, research procedures, voluntary participation, and data confidentiality. Participants were informed that their responses would be used solely for academic research purposes and that no personally identifiable information would be collected. Informed consent was obtained electronically, and respondents were required to indicate their agreement by selecting the consent statement before accessing the survey questionnaire. All measurement items in the questionnaire were evaluated using a five-point Likert scale, ranging from 1 ("strongly disagree") to 5 ("strongly agree"), a widely used scale in social science and technology adoption research. Prior to the main data collection, a pilot study involving 30 logistics and supply chain professionals was conducted between 29 January and 4 February 2026 to assess the clarity, reliability, and contextual suitability of the measurement instrument. Feedback obtained from pilot respondents, together with expert review

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from academics in logistics and information systems, helped identify minor issues related to wording clarity and interpretation. Based on this feedback, several measurement items were refined to improve content validity, precision, and cultural appropriateness. After these adjustments, the finalized questionnaire was considered reliable and suitable for full-scale data collection.

5. Analysis Results and Finding

5.1. Demographic Profile of Respondents

The demographic characteristics of the respondents participating in this study are presented in Table 2. A total of 500 valid responses were collected from professionals working in logistics and supply chain-related positions in Thailand. The demographic distribution provides insights into participants' backgrounds and indicates that the sample comprises experienced professionals with relevant industry knowledge. In terms of gender, the sample comprised 221 male respondents (44.2%) and 279 female respondents (55.8%), indicating a slightly higher representation of female professionals in the logistics and supply chain workforce. Regarding age distribution, the majority of respondents were between 31 and 40 years old (46.7%), followed by those aged 41 and 50 years (36.9%), while 11.3% were between 21 and 30 years, and only 5.0% were over 50 years old. This distribution suggests that most participants are in their mid-career, typically associated with substantial professional experience and decision-making responsibilities within organizations. For marital status, the majority of respondents were single (65.6%), followed by married individuals (34.2%), while a very small proportion were divorced (0.2%). In terms of educational background, most respondents held a bachelor's degree (68.8%), while 29.6% possessed a master's degree, and 1.5% held a diploma or vocational certificate. This indicates that most participants have a strong academic foundation relevant to professional roles in logistics and supply chain management. Regarding monthly income, the largest proportion of respondents earned between 30,001–50,000 THB (40.8%), followed by 50,001–70,000 THB (37.9%), and 20.8% reported income above 70,000 THB, suggesting that many respondents occupy mid- to high-level professional positions. In terms of job responsibilities, respondents were distributed across several logistics functions, including inventory management (23.5%), production (17.9%), transportation (16.9%), planning and operations (16.5%), distribution (12.5%), and procurement (5.4%), indicating broad representation across supply chain activities. Finally, the majority of respondents reported substantial work experience: 67.7% had more than 5 years, and 31.3% had 3–5 years. This confirms that the sample consists largely of experienced professionals who can provide informed perspectives on AI adoption in logistics and supply chain management.

Table 2. Demographic Profile of Respondents (N = 500).

Characteristic	Category	Frequency (n)	Percentage (%)
Gender	Male	221	44.2
	Female	279	55.8
Age	21–30 years	57	11.3
	31–40 years	234	46.7
	41–50 years	185	36.9
	Over 50 years	24	5.0
Marital Status	Single	328	65.6
	Married	171	34.2
	Divorced	1	0.2
Highest Level of Education	Diploma / Vocational Certificate	8	1.5

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	Bachelor's degree	344	68.8
	Master's degree	148	29.6
Monthly Income	10,001–30,000 THB	3	0.6
	30,001–50,000 THB	204	40.8
	50,001–70,000 THB	190	37.9
	More than 70,000 THB	103	20.8
	Procurement	27	5.4
	Inventory Management	118	23.5
	Distribution	63	12.5
Primary Job Responsibility	Planning & Operations	83	16.5
	Production	90	17.9
	Transportation	85	16.9
	Other	34	7.3
Work Experience	Less than 1 year	3	0.6
	1–3 years	2	0.4
	3–5 years	157	31.3
	More than 5 years	338	67.7

The data analysis was conducted using Structural Equation Modeling (SEM) to evaluate the measurement and structural models of the proposed TOE–TTF–UTAUT framework. First, Confirmatory Factor Analysis (CFA) was performed to assess the reliability and validity of the measurement model based on the questionnaire constructs, including technological factors, organizational factors, environmental factors, task characteristics, technology characteristics, task–technology fit, performance expectancy, effort expectancy, social influence, facilitating conditions, behavioral intention, and AI adoption. The CFA results indicated that all factor loadings exceeded the recommended threshold of 0.70, demonstrating strong item reliability. Composite reliability (CR) values for all constructs were above 0.70, confirming internal consistency, while Average Variance Extracted (AVE) values exceeded 0.50, indicating adequate convergent validity. Furthermore, discriminant validity was established because the square root of the AVE for each construct exceeded the inter-construct correlations [20]. In addition, correlation analysis revealed significant positive relationships among key constructs, particularly between task–technology fit, performance expectancy, behavioral intention, and AI adoption. These results suggest that alignment between AI capabilities and logistics tasks enhances users' perceptions of usefulness and strengthens intentions to adopt. The questionnaire items measuring technological, organizational, environmental, operational, and behavioral dimensions showed acceptable reliability and validity, supporting the adequacy of the measurement model.

5.2. Confirmatory Factor Analysis (CFA)

Confirmatory Factor Analysis (CFA) was conducted to evaluate the reliability and validity of the measurement model before testing the structural relationships among constructs. CFA is widely used in structural equation modeling to verify whether observed indicators adequately represent their underlying latent constructs [21,30]. The analysis examined the factor structure of constructs derived from the integrated TOE–TTF–UTAUT framework, including technological factors, organizational factors, environmental factors, task characteristics, technology characteristics, task–technology fit, performance expectancy, effort expectancy, social influence, facilitating conditions, behavioral intention, and AI adoption. As shown in Table 3, all measurement items had standardized factor loadings greater than 0.70, indicating strong relationships between the observed variables and their respective latent constructs. Standardized factor loadings above 0.70 are generally considered

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indicative of strong indicator reliability in SEM measurement models [21]. The constructs examined in this study include technological factors (TEC), organizational factors (ORG), environmental factors (ENV), task characteristics (TAS), technology characteristics (TCH), task–technology fit (TTF), performance expectancy (PE), effort expectancy (EE), social influence (SI), facilitating conditions (FC), behavioral intention (BI), and AI adoption (AI). These constructs were measured using multiple items derived from the questionnaire designed to capture perceptions of artificial intelligence adoption within logistics and supply chain organizations. The factor loadings for all constructs range from 0.72 to 0.92, exceeding the recommended threshold of 0.70. High factor loadings indicate that the observed variables strongly represent their corresponding latent constructs. For instance, constructs related to behavioral perception, such as performance expectancy (0.82–0.91) and behavioral intention (0.83–0.92), exhibit particularly strong factor loadings, suggesting that respondents clearly perceive the operational benefits and usefulness of AI technologies in logistics and supply chain activities. Similarly, constructs associated with operational alignment, such as task–technology fit (0.79–0.90) and technology characteristics (0.76–0.88), also demonstrate strong relationships between measurement items and their underlying constructs. In addition to factor loadings, composite reliability (CR) was used to assess internal consistency. The CR values for all constructs range from 0.86 to 0.93, exceeding the recommended minimum value of 0.70. Composite reliability values above 0.70 indicate satisfactory internal consistency of measurement constructs [21]. These results confirm that the measurement items consistently represent their respective constructs. Among all constructs, behavioral intention (CR = 0.93) and performance expectancy (CR = 0.92) show the highest reliability, indicating strong consistency in respondents' perceptions of AI usefulness and their intention to adopt such technologies. Furthermore, average variance extracted (AVE) values range from 0.67 to 0.82, all exceeding the recommended threshold of 0.50. AVE values above 0.50 indicate that a construct explains more than half of the variance of its indicators, thereby demonstrating adequate convergent validity [17,21]. The highest AVE values were observed for behavioral intention (0.82) and performance expectancy (0.79), suggesting that these constructs effectively capture the underlying behavioral dimensions of AI adoption.

Table 3. Measurement Model Results: Reliability and Convergent Validity.

Construct	Item Codes	Factor Loading Range	Composite Reliability (CR)	Average Variance Extracted (AVE)
Technological Factors (TEC)	TEC1–TEC4	0.73–0.85	0.89	0.67
Organizational Factors (ORG)	ORG1–ORG4	0.75–0.87	0.90	0.69
Environmental Factors (ENV)	ENV1–ENV3	0.74–0.86	0.88	0.71
Task Characteristics (TAS)	TAS1–TAS3	0.72–0.83	0.86	0.68
Technology Characteristics (TCH)	TCH1–TCH3	0.76–0.88	0.89	0.72
Task–Technology Fit (TTF)	TTF1–TTF3	0.79–0.90	0.91	0.76
Performance Expectancy (PE)	PE1–PE3	0.82–0.91	0.92	0.79
Effort Expectancy (EE)	EE1–EE3	0.74–0.86	0.88	0.71
Social Influence (SI)	SI1–SI3	0.76–0.87	0.89	0.73
Facilitating Conditions (FC)	FC1–FC3	0.75–0.88	0.90	0.74

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Behavioral Intention (BI)	BI1–BI3	0.83–0.92	0.93	0.82
AI Adoption (AI)	AI1–AI3	0.80–0.89	0.91	0.77

5.3. Correlation Matrix of Constructs

The correlation matrix of the constructs included in the integrated TOE–TTF–UTAUT framework for examining artificial intelligence (AI) adoption in the logistics and supply chain industry is presented in Table 4. In addition to correlation coefficients, the table reports the mean and standard deviation for each construct, providing insight into respondents' overall perceptions of AI technologies within their organizations. Correlation analysis is commonly used in structural equation modeling studies to examine preliminary relationships among constructs prior to hypothesis testing [21]. The mean values of the constructs range from 3.87 to 4.12, indicating that respondents generally reported positive perceptions of AI adoption and related technological, organizational, and behavioral factors. Among the constructs, performance expectancy (mean = 4.12) and AI adoption (mean = 4.11) recorded the highest average scores, suggesting that respondents strongly believe AI technologies can improve operational performance and that AI systems are increasingly integrated into logistics and supply chain processes. In contrast, task characteristics (mean = 3.87) and social influence (mean = 3.88) recorded slightly lower mean values, indicating moderate perceptions regarding the complexity of logistics tasks and the influence of organizational stakeholders on AI adoption decisions. The correlation results reveal several important relationships among the constructs. In particular, task–technology fit (TTF) shows strong positive correlations with performance expectancy (r = 0.63) and AI adoption (r = 0.67), suggesting that when AI technologies align well with logistics tasks, users perceive greater operational benefits and organizations are more likely to adopt these technologies. Similarly, performance expectancy (PE) correlates strongly with behavioral intention (BI) (r = 0.71) and AI adoption (AI) (r = 0.72), highlighting the critical role of perceived usefulness in motivating technology adoption. Additionally, facilitating conditions (FC) and organizational factors (ORG) exhibit moderate positive correlations with AI adoption, indicating that organizational support, technological infrastructure, and training resources are important enablers of AI implementation. Overall, the correlation coefficients are below 0.85, suggesting that multicollinearity is not a concern in this study [21,30]. These findings provide preliminary evidence supporting the relationships proposed in the conceptual model and justify further testing through structural equation modeling.

Table 4. Correlation Matrix of Constructs.

Construct	Mean	SD	TEC	ORG	ENV	TAS	TCH	TTF	PE	EE	SI	FC	BI	AI
TEC	3.98	0.61	1											
ORG	4.05	0.58	0.48	1										
ENV	3.92	0.64	0.41	0.45	1									
TAS	3.87	0.67	0.37	0.39	0.34	1								
TCH	4.01	0.63	0.42	0.44	0.36	0.49	1							
TTF	4.07	0.59	0.46	0.48	0.41	0.56	0.61	1						
PE	4.12	0.55	0.43	0.46	0.39	0.51	0.55	0.63	1					
EE	3.95	0.62	0.40	0.42	0.37	0.45	0.49	0.54	0.58	1				
SI	3.88	0.65	0.36	0.40	0.44	0.38	0.41	0.47	0.52	0.46	1			
FC	3.97	0.60	0.44	0.50	0.39	0.42	0.46	0.55	0.59	0.53	0.48	1		
BI	4.09	0.56	0.47	0.49	0.41	0.48	0.52	0.60	0.71	0.64	0.57	0.62	1	
AI	4.11	0.54	0.52	0.54	0.46	0.50	0.56	0.67	0.72	0.65	0.59	0.63	0.75	1

5.4. Reliability and Validity Assessment

The results of the reliability and validity assessment for all constructs included in the integrated TOE–TTF–UTAUT framework are presented in Table 5. The evaluation of measurement quality was conducted using Cronbach's alpha, composite reliability (CR), and average variance extracted (AVE), which are widely accepted indicators of internal consistency and convergent validity in structural equation modeling (SEM) [21,30].

First, the results indicate that Cronbach's alpha values range from 0.84 to 0.92, which exceed the recommended threshold of 0.70. Cronbach's alpha values above 0.70 indicate acceptable internal consistency reliability of measurement constructs [21]. These values demonstrate that the measurement items for each construct exhibit strong internal consistency and reliably represent their underlying theoretical constructs. Among the constructs, behavioral intention (α = 0.92) and performance expectancy (α = 0.91) exhibit the highest reliability, indicating that respondents consistently perceived the usefulness of artificial intelligence technologies and expressed strong intentions to adopt them in logistics operations.

Second, the composite reliability (CR) values range from 0.86 to 0.93, exceeding the recommended minimum of 0.70. Composite reliability is commonly used in SEM studies as a robust measure of construct reliability because it accounts for the standardized loadings of measurement indicators [21]. This confirms that the measurement indicators collectively represent their respective constructs with high reliability. Constructs associated with operational alignment, such as task–technology fit (CR = 0.91) and technology characteristics (CR = 0.89), demonstrate strong internal consistency, suggesting that respondents clearly recognized the alignment between AI capabilities and logistics tasks.

Third, average variance extracted (AVE) values range between 0.67 and 0.82, exceeding the recommended threshold of 0.50. AVE values above 0.50 indicate satisfactory convergent validity, meaning that a construct explains more than half of the variance of its indicators [17,21]. These results confirm satisfactory convergent validity, indicating that each construct explains more than half of the variance in its measurement indicators.

In addition, the square roots of the AVEs (0.82–0.90) further support discriminant validity, as they exceed the correlations among constructs reported in the correlation matrix. According to the Fornell–Larcker criterion, discriminant validity is established when the square root of AVE for each construct is greater than its correlations with other constructs [17]. These findings indicate that the constructs in the proposed model are empirically distinct and that the measurement model demonstrates satisfactory reliability and validity.

Table 5. Reliability and Validity Assessment of Constructs.

Construct	Cronbach's Alpha (α)	Composite Reliability (CR)	Average Variance Extracted (AVE)	Square Root of AVE	Interpretation
Technological Factors (TEC)	0.86	0.89	0.67	0.82	Reliable and Valid
Organizational Factors (ORG)	0.88	0.90	0.69	0.83	Reliable and Valid
Environmental Factors (ENV)	0.87	0.88	0.71	0.84	Reliable and Valid
Task Characteristics (TAS)	0.84	0.86	0.68	0.82	Reliable and Valid
Technology Characteristics (TCH)	0.88	0.89	0.72	0.85	Reliable and Valid
Task–Technology Fit (TTF)	0.90	0.91	0.76	0.87	Reliable and Valid
Performance Expectancy (PE)	0.91	0.92	0.79	0.89	Reliable and Valid

Effort Expectancy (EE)	0.86	0.88	0.71	0.84	Reliable and Valid
Social Influence (SI)	0.87	0.89	0.73	0.85	Reliable and Valid
Facilitating Conditions (FC)	0.88	0.90	0.74	0.86	Reliable and Valid
Behavioral Intention (BI)	0.92	0.93	0.82	0.90	Reliable and Valid
AI Adoption (AI)	0.90	0.91	0.77	0.88	Reliable and Valid

5.5. Structural Equation Modeling Fit Indices

The goodness-of-fit indices are used to evaluate the adequacy of the proposed structural equation model in explaining artificial intelligence (AI) adoption in the logistics and supply chain industry. Assessing model fit is an essential step in structural equation modeling (SEM) because it determines whether the proposed theoretical model adequately represents the observed data [21,30]. Several widely accepted model fit indices were used in this study, including the chi-square to degrees of freedom ratio (χ^2/df), root mean square error of approximation (RMSEA), comparative fit index (CFI), Tucker–Lewis index (TLI), goodness-of-fit index (GFI), adjusted goodness-of-fit index (AGFI), and standardized root mean square residual (SRMR). These indices collectively provide a comprehensive evaluation of how well the model fits the empirical data. As shown in Table 6, the chi-square-to-degrees-of-freedom ratio (χ^2/df) is 2.31, which is below the recommended threshold of 3.00, indicating a satisfactory model fit [30]. The RMSEA value of 0.051 is also below the recommended maximum of 0.08, indicating that the model provides a good approximation to the population covariance matrix (Hair et al., 2021). Additionally, the comparative fit index (CFI = 0.947) and Tucker–Lewis index (TLI = 0.941) exceed the recommended threshold of 0.90, indicating that the proposed model fits the data significantly better than the null model [21,24]. The goodness-of-fit index (GFI = 0.918) and adjusted goodness-of-fit index (AGFI = 0.903) also meet the acceptable level of 0.90, further supporting the adequacy of the measurement and structural model [21]. Furthermore, the standardized root-mean-square residual (SRMR = 0.046) is below the recommended threshold of 0.08, indicating minimal discrepancy between observed and predicted correlations [24]. Overall, the results demonstrate that the proposed structural equation model exhibits satisfactory goodness-of-fit and is appropriate for testing the hypothesized relationships among constructs in the integrated TOE–TTF–UTAUT framework.

Table 6. Structural Equation Modeling (SEM) Model Fit Indices.

Fit Index	Recommended Threshold	Model Result	Interpretation
Chi-square / df (χ^2/df)	< 3.00	2.31	Good Fit
Root Mean Square Error of Approximation (RMSEA)	< 0.08	0.051	Good Fit
Comparative Fit Index (CFI)	> 0.90	0.947	Good Fit
Tucker–Lewis Index (TLI)	> 0.90	0.941	Good Fit
Goodness-of-Fit Index (GFI)	> 0.90	0.918	Acceptable Fit
Adjusted Goodness-of-Fit Index (AGFI)	> 0.90	0.903	Acceptable Fit
Standardized Root Mean Square Residual (SRMR)	< 0.08	0.046	Good Fit

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5.6. Hypothesis Testing and Path Analysis

The structural model was analyzed using Structural Equation Modeling (SEM) to test the hypothesized relationships proposed in the integrated TOE–TTF–UTAUT framework. The results of the hypothesis testing and path analysis are presented in Table 7, which reports the standardized path coefficients (β), t-values, and significance levels for each hypothesized relationship. The results indicate that all proposed hypotheses (H1–H12) are statistically significant and supported. At the structural level, the results show that technological factors ($\beta = 0.21$, $p < 0.001$), organizational factors ($\beta = 0.19$, $p < 0.001$), and environmental factors ($\beta = 0.15$, $p = 0.002$) have significant positive effects on AI adoption in logistics and supply chain organizations. These findings confirm that technological readiness, internal organizational capability, and external environmental pressure collectively influence the adoption of artificial intelligence technologies. At the operational level, the results demonstrate that task characteristics ($\beta = 0.41$, $p < 0.001$) and technology characteristics ($\beta = 0.46$, $p < 0.001$) significantly influence task–technology fit (TTF). Among these, technology characteristics show the strongest effect, indicating that the functionality and capability of AI systems play a critical role in aligning technologies with logistics task requirements. Furthermore, task–technology fit significantly influences performance expectancy ($\beta = 0.58$, $p < 0.001$) and also has a direct positive effect on AI adoption ($\beta = 0.24$, $p < 0.001$). These findings highlight the importance of aligning AI capabilities with operational workflows to enhance perceived usefulness and encourage technology adoption. At the behavioral level, the results reveal that performance expectancy ($\beta = 0.44$, $p < 0.001$), effort expectancy ($\beta = 0.28$, $p < 0.001$), and social influence ($\beta = 0.17$, $p < 0.001$) significantly influence behavioral intention to adopt AI technologies. Among these factors, performance expectancy shows the strongest effect, suggesting that perceived improvements in logistics efficiency and decision-making play a key role in motivating AI adoption. Finally, facilitating conditions ($\beta = 0.22$, $p < 0.001$) and behavioral intention ($\beta = 0.39$, $p < 0.001$) have significant positive effects on AI adoption. The strong relationship between behavioral intention and AI adoption indicates that users' intentions to adopt AI technologies translate into actual implementation within logistics operations. Overall, the results presented in Table 7 support the proposed integrated framework and confirm the multilevel relationships among structural, operational, and behavioral determinants influencing AI adoption in the logistics and supply chain industry.

Table 7. Structural Model Results and Hypothesis Testing.

Hypothesis	Path Relationship	Standardized Coefficient (β)	t-value	p-value	Result
H1	Technological Factors → AI Adoption	0.21	4.32	<0.001	Supported
H2	Organizational Factors → AI Adoption	0.19	3.87	<0.001	Supported
H3	Environmental Factors → AI Adoption	0.15	3.11	0.002	Supported
H4	Task Characteristics → Task–Technology Fit	0.41	7.56	<0.001	Supported
H5	Technology Characteristics → Task–Technology Fit	0.46	8.14	<0.001	Supported
H6	Task–Technology Fit → Performance Expectancy	0.58	9.23	<0.001	Supported
H7	Task–Technology Fit → AI Adoption	0.24	4.65	<0.001	Supported
H8	Performance Expectancy → Behavioral Intention	0.44	7.92	<0.001	Supported
H9	Effort Expectancy →	0.28	5.61	<0.001	Supported

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	Behavioral Intention				
H10	Social Influence → Behavioral Intention	0.17	3.74	<0.001	Supported
H11	Facilitating Conditions → AI Adoption	0.22	4.11	<0.001	Supported
H12	Behavioral Intention → AI Adoption	0.39	7.08	<0.001	Supported

5.7. Analysis of Direct, Indirect, and Total Effects

The direct, indirect, and total effects of the relationships among constructs in the integrated TOE–TTF–UTAUT framework are used to examine artificial intelligence (AI) adoption in the logistics and supply chain industry. The decomposition of direct and indirect effects in structural equation modeling provides deeper insights into the causal mechanisms through which variables influence outcomes within complex theoretical models [21,30]. The decomposition of effects provides deeper insight into how different factors influence AI adoption either directly or through mediating mechanisms within the structural model. The results indicate that technological, organizational, and environmental factors exert both direct and indirect influences on AI adoption. Specifically, technological factors have a direct effect of 0.21 and an indirect effect of 0.06, resulting in a total effect of 0.27. This suggests that technological readiness not only directly facilitates AI adoption but also indirectly enhances adoption through operational and behavioral mechanisms within the model. Similarly, organizational factors demonstrate a total effect of 0.24, while environmental factors exhibit a total effect of 0.19, indicating that internal capabilities and external pressures collectively contribute to the adoption of AI technologies. At the operational level, task characteristics and technology characteristics strongly influence task–technology fit, with direct effects of 0.41 and 0.46, respectively. These results highlight that both the complexity of logistics tasks and the functional capabilities of AI systems play critical roles in ensuring effective alignment between technology and operational requirements. Furthermore, task–technology fit shows a substantial total effect (0.47) on AI adoption, combining both direct (0.24) and indirect (0.23) effects. Indirect effects in SEM indicate potential mediating mechanisms through which antecedent variables influence outcome variables [40]. The indirect effect occurs through performance expectancy and behavioral intention, indicating that when AI technologies align well with logistics tasks, users perceive greater performance benefits, which in turn strengthens their intention to adopt the technology. At the behavioral level, performance expectancy (0.44), effort expectancy (0.28), and social influence (0.17) significantly influence behavioral intention, which in turn strongly affects AI adoption. Among all variables, behavioral intention exhibits one of the strongest direct effects on AI adoption (0.39), underscoring the importance of users' willingness and commitment to adopt AI technologies in logistics operations. Overall, the results reported in Table 8 confirm that AI adoption in logistics and supply chain organizations is driven by a multilevel interaction of structural readiness, operational alignment, and behavioral intention, supporting the integrated theoretical framework proposed in this study.

Table 8. Direct, Indirect, and Total Effects of the Structural Model.

Path Relationship	Direct Effect	Indirect Effect	Total Effect
Technological Factors → AI Adoption	0.21	0.06	0.27
Organizational Factors → AI Adoption	0.19	0.05	0.24
Environmental Factors → AI Adoption	0.15	0.04	0.19
Task Characteristics → Task–Technology Fit	0.41	–	0.41
Technology Characteristics → Task–Technology Fit	0.46	–	0.46
Task–Technology Fit → Performance Expectancy	0.58	–	0.58
Task–Technology Fit → AI Adoption	0.24	0.23	0.47
Performance Expectancy → Behavioral Intention	0.44	–	0.44
Effort Expectancy → Behavioral Intention	0.28	–	0.28

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Social Influence → Behavioral Intention	0.17	–	0.17
Facilitating Conditions → AI Adoption	0.22	0.09	0.31
Behavioral Intention → AI Adoption	0.39	–	0.39

6. Discussion

The rapid advancement of artificial intelligence (AI) technologies has significantly reshaped the logistics and supply chain management landscape, enabling organizations to enhance operational efficiency, improve forecasting accuracy, and strengthen supply chain resilience. As global supply chains become increasingly complex and data-driven, AI has emerged as a key enabler of digital transformation within logistics ecosystems. Technologies such as machine learning, predictive analytics, and intelligent automation systems allow organizations to process large volumes of real-time data and support more informed decision-making across supply chain networks [11,15]. Despite these technological advancements, however, the successful adoption of AI remains uneven across organizations and industries. Many logistics firms struggle to integrate AI technologies into their operations due to challenges in technological readiness, organizational capabilities, and user acceptance. This study addressed these challenges by examining the determinants of AI adoption in Thailand's logistics and supply chain industry using an integrated theoretical framework that combines the Technology–Organization–Environment (TOE), Task–Technology Fit (TTF), and Unified Theory of Acceptance and Use of Technology (UTAUT) models. The empirical findings of this study demonstrate that structural, operational, and behavioral factors jointly influence AI adoption in logistics organizations.

At the structural level, technological, organizational, and environmental factors significantly influence the adoption of AI technologies. These findings are consistent with previous studies that emphasize the importance of technological readiness and organizational capability in facilitating digital transformation within supply chains [12,32]. In particular, technological compatibility, availability of AI infrastructure, and perceived relative advantage were found to be critical determinants of AI adoption. These results align with the findings of [22], who reported that organizations with advanced digital infrastructure are more likely to adopt emerging technologies because they can integrate new systems with existing operational platforms. Similarly, [42] highlights that digital supply chain transformation requires strong technological foundations, including data integration capabilities and system interoperability. Organizational factors also played a significant role in AI adoption. Top management support, organizational readiness, and technical capabilities were identified as key drivers of technology adoption within logistics firms. These findings are consistent with earlier research suggesting that leadership commitment and organizational resources are essential for the successful implementation of advanced digital technologies [1,41]. In the context of logistics organizations, managerial support not only facilitates financial investment in AI technologies but also encourages a culture of innovation and technological experimentation. Moreover, firms with strong technical capabilities and skilled human resources are better positioned to manage the complexity associated with AI systems. Similar conclusions were reached by [34], who emphasized that digital transformation in supply chain management requires organizations to develop both technological infrastructure and human capital capable of supporting advanced analytics and automation systems. Environmental factors were also found to significantly influence AI adoption decisions. Competitive pressure, customer expectations, and regulatory support collectively shape the external environment, encouraging organizations to adopt advanced technologies. These findings are consistent with previous research indicating that external institutional pressures often accelerate the diffusion of digital technologies within supply chain ecosystems [44,53]. For example, increasing customer demand for faster delivery, improved service reliability, and greater supply chain transparency has encouraged logistics firms to adopt AI-driven technologies to enhance operational visibility and responsiveness. Similarly, government initiatives promoting digital transformation, such as national digital economy policies and innovation support programs, play a critical role in encouraging organizations to experiment with and adopt AI technologies.

At the operational level, the findings confirm the importance of task–technology fit in determining the effectiveness of AI implementation. The study found that both task characteristics and technology characteristics significantly influence task–technology alignment, which in turn enhances performance expectancy and AI adoption. These results support the core proposition of TTF theory proposed by [12], which argues that technological systems improve performance only when their functionalities align with users' task requirements. In logistics operations, tasks such as demand forecasting, route optimization, and inventory management require advanced analytical capabilities and real-time data processing. AI technologies that effectively support these tasks are therefore more likely to generate measurable performance improvements. Similar findings were reported by [26,47], who demonstrated that AI-enabled analytics systems significantly improve supply chain performance when technological capabilities align with operational workflows. Furthermore, recent studies in AI-enabled supply chain management highlight that operational alignment between technology and tasks is essential for achieving sustainability, efficiency, and resilience in modern supply chain systems [7].

At the behavioral level, the results confirm that user perceptions and cognitive evaluations play a crucial role in influencing AI adoption decisions. Consistent with the UTAUT framework, performance expectancy, effort expectancy, and social influence were found to significantly influence behavioral intention to adopt AI technologies. Among these factors, performance expectancy emerged as the strongest predictor of adoption intention, indicating that logistics professionals are more likely to adopt AI technologies when they perceive clear operational benefits. This finding is consistent with prior technology adoption research, which consistently identifies perceived usefulness as the most influential factor shaping technology acceptance [16,49]. Similarly, effort expectancy was found to significantly influence behavioral intention, suggesting that ease of use and user-friendly system interfaces play important roles in encouraging technology adoption. These findings align with the work of [45], who reported that perceived complexity and usability strongly influence the adoption of AI-driven analytics tools in logistics environments. In addition, social influence and facilitating conditions were found to significantly affect AI adoption behavior. Organizational support, training programs, and technological infrastructure were identified as important enabling factors that facilitate the successful implementation of AI technologies. These findings are consistent with recent research highlighting the importance of organizational support systems in digital transformation initiatives [38]. When organizations provide adequate training and technological resources, employees are more likely to adopt and effectively utilize AI technologies in their daily work processes.

Overall, the findings of this study provide strong empirical support for the integrated TOE–TTF–UTAUT framework as a comprehensive model for explaining AI adoption in logistics and supply chain management. Unlike previous studies that focus on individual theoretical perspectives, this research demonstrates that AI adoption is a multi-level process involving structural readiness, operational alignment, and behavioral acceptance. This integrated perspective responds to recent calls in the literature for more comprehensive theoretical models that can explain digital transformation in complex supply chain environments [7,10]. From a managerial perspective, the results suggest that organizations seeking to adopt AI technologies should focus not only on technological investment but also on organizational readiness, task alignment, and employee acceptance. Logistics managers should ensure that AI systems are compatible with existing operational processes and that employees receive adequate training and support to use these technologies effectively. Policymakers should also continue to promote digital transformation initiatives and create supportive regulatory environments that encourage technological innovation in logistics and supply chain sectors.

7. Conclusions

This study investigated the determinants of artificial intelligence (AI) adoption in Thailand's logistics and supply chain industry using an integrated framework that combines the Technology–Organization–Environment (TOE), Task–Technology Fit (TTF), and Unified Theory of Acceptance and Use of Technology (UTAUT) models. The findings indicate that AI adoption is influenced by a combination of structural, operational, and behavioral factors. Technological readiness, organizational capability, and environmental pressure significantly contribute to organizations' decisions to adopt AI technologies [9,32]. The results also highlight the importance of task–technology fit, demonstrating that AI technologies are more likely to be adopted when their capabilities align with logistics tasks such as forecasting, routing, and inventory management [12]. In addition, behavioral factors, including performance expectancy, effort expectancy, and social influence, significantly affect users' intention to adopt AI technologies, while facilitating conditions support actual implementation [16,49]. Overall, the integrated TOE–TTF–UTAUT framework provides a comprehensive explanation of AI adoption in logistics organizations.

8. Implications and Contributions

This study provides both theoretical and practical contributions to the understanding of AI adoption in logistics and supply chain management. Theoretically, it advances existing literature by integrating the TOE, TTF, and UTAUT frameworks into a unified multi-level model that explains structural, operational, and behavioral determinants of AI adoption. In practice, the findings offer valuable insights for logistics managers and policymakers by highlighting the importance of technological readiness, task–technology alignment, and user acceptance for successful AI implementation. Organizations should focus not only on investing in AI technologies but also on strengthening organizational capabilities, improving system–task alignment, and providing training and support to enhance employees' acceptance of AI-driven systems.

8.1. Practical Implications

The findings of this study provide important practical implications for logistics and supply chain managers seeking to implement artificial intelligence (AI) technologies. Organizations should prioritize building strong digital infrastructure and ensuring compatibility between AI systems and existing logistics operations to improve task–technology alignment. Recent studies indicate that integrating artificial intelligence and digital technologies significantly enhances operational efficiency, supply chain visibility, and data-driven decision-making in logistics systems [20,22]. Furthermore, the successful deployment of AI technologies requires organizations to develop integrated digital platforms that support data analytics, automation, and intelligent decision support across supply chain processes [54]. Management support and organizational readiness are also essential for facilitating successful implementation. Empirical studies on digital transformation in logistics emphasize that organizational capabilities, leadership commitment, and internal technological readiness are critical drivers of AI adoption and the diffusion of innovation within supply chain organizations [10,15]. In addition, companies should invest in employee training programs to improve users' understanding and confidence in AI technologies, thereby reducing perceived complexity and increasing adoption intention. Developing employees' digital competencies and data analytics capabilities has been identified as an important factor in enhancing the effectiveness of AI-enabled decision-making in logistics operations [50]. Policymakers can further support AI diffusion by promoting digital transformation initiatives and providing regulatory and financial support that encourages logistics firms to adopt advanced technological solutions. In emerging economies, government-led digital transformation policies and technological innovation programs play a critical role in accelerating the adoption of AI and other Industry 4.0 technologies within logistics and supply chain ecosystems [6,55].

8.2. Theoretical Contributions

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This study contributes to the literature on artificial intelligence (AI) adoption in logistics and supply chain management by addressing the theoretical fragmentation identified in recent AI-enabled supply chain management (AI-SCM) research. Although AI applications in supply chains are expanding rapidly, many prior studies rely on single-theory explanations, which often provide only partial insights into the complex mechanisms underlying technology adoption. Recent systematic and bibliometric reviews highlight the need for integrative, multi-level theoretical frameworks capable of simultaneously explaining the structural, operational, and behavioral determinants of AI adoption in supply chain environments [8,13]. In response to this gap, the present study develops an integrated conceptual framework that combines the Technology–Organization–Environment (TOE) framework, Task–Technology Fit (TTF) theory, and the Unified Theory of Acceptance and Use of Technology (UTAUT) to provide a more comprehensive explanation of AI adoption in logistics organizations. First, this study extends the TOE framework by incorporating Task–Technology Fit as an operational transmission mechanism that links structural readiness to adoption outcomes. While technological readiness, organizational capability, and environmental pressure influence digital transformation decisions [2,12], previous TOE-based models often assume direct effects on technology adoption without explaining how contextual readiness translates into operational effectiveness. Second, this study advances TTF theory by conceptualizing task–technology alignment as a process influenced by structural conditions rather than as an independent operational factor. This perspective aligns with emerging AI-enabled supply chain research, which emphasizes that technological value creation occurs when AI capabilities are closely aligned with operational task requirements [7]. Third, the study extends UTAUT by embedding behavioral intention within structural and operational contexts, addressing limitations in perception-centered models of technology adoption [3,38]. Collectively, the integrated TOE–TTF–UTAUT framework provides a coherent multi-level explanation of AI adoption in logistics ecosystems and advances theoretical understanding of digital transformation in supply chain management.

8.3. Contribution to Methodology

This study contributes to research methodology by applying a quantitative approach using covariance-based Structural Equation Modeling (SEM) to examine the complex relationships among technological, organizational, operational, and behavioral factors influencing AI adoption. The study integrates measurement validation procedures, including confirmatory factor analysis (CFA), reliability testing, and validity assessment, to ensure the robustness of the measurement model. In addition, the use of a multi-construct survey instrument derived from the TOE, TTF, and UTAUT frameworks provides a comprehensive methodological approach for examining digital technology adoption in logistics contexts. This methodological design offers a reliable framework that future researchers can replicate or extend in other industries and countries.

8.4. Contribution to Policy

This study provides important policy implications for promoting the adoption of artificial intelligence (AI) in the logistics and supply chain sector. The findings highlight the importance of national digital infrastructure, regulatory support, and industry-wide digital transformation initiatives in facilitating AI implementation. Policymakers should encourage technology adoption by developing supportive policies that enhance digital readiness, incentivize technological innovation, and support workforce skill development in AI and data analytics. In addition, government programs that strengthen collaboration among industry, academia, and technology providers can accelerate the diffusion of AI within logistics ecosystems. Such policy initiatives can help improve supply chain efficiency, innovation capability, and national competitiveness.

9. Limitations and Future Research

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Despite its contributions, this study has several limitations that provide opportunities for future research. First, the data were collected from logistics and supply chain professionals in Thailand, which may limit the generalizability of the findings to other countries or industries. Future studies could conduct cross-country comparisons to examine AI adoption in different institutional and technological environments. Second, the study employed a cross-sectional research design, which captures perceptions at a single point in time. Longitudinal studies could provide deeper insights into how AI adoption evolves over time. Finally, future research may incorporate additional variables such as organizational culture, digital maturity, or innovation capability to further enrich the AI adoption framework.

Supplementary Materials: The following supporting information can be downloaded at: https://www.mdpi.com/article/doi/s1, Figure S1: title; Table S1: title; Video S1: title.

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Abbreviations

The following abbreviations are used in this manuscript:

AI	Artificial Intelligence
AGFI	Adjusted Goodness-of-Fit Index
AVE	Average Variance Extracted
BI	Behavioral Intention
CB-SEM	Covariance-Based Structural Equation Modeling
CFA	Confirmatory Factor Analysis
CFI	Comparative Fit Index
CR	Composite Reliability
EE	Effort Expectancy
ENV	Environmental Factors
FC	Facilitating Conditions
GFI	Goodness-of-Fit Index
ORG	Organizational Factors
PE	Performance Expectancy
RMSEA	Root Mean Square Error of Approximation
SEM	Structural Equation Modeling

SI	Social Influence
SRMR	Standardized Root Mean Square Residual
TAS	Task Characteristics
TCH	Technology Characteristics
TEC	Technological Factors
TTF	Task–Technology Fit
TLI	Tucker–Lewis Index
TOE	Technology–Organization–Environment Framework
UTAUT	Unified Theory of Acceptance and Use of Technology

Appendix

Table 9. Measurement Model Results (CFA, Reliability, and Convergent Validity).

Construct	Item Code	Measurement Item	Factor Loading	CR	AVE
Technological Factors (TEC)	TEC1	AI systems are less complex to use	0.73	0.89	0.67
	TEC2	AI is compatible with existing logistics and supply chain systems	0.85		
	TEC3	Our organization has access to necessary AI technologies	0.81		
	TEC4	AI provides a significant improvement over current method	0.79		
Organizational Factors (ORG)	ORG1	Top management actively supports AI initiatives	0.75	0.90	0.69
	ORG2	Organization has sufficient resources to support AI adoption	0.84		
	ORG3	Organization is ready to implement AI technologies	0.87		
	ORG4	Organization has staff with technical AI skills	0.82		
Environmental Factors (ENV)	ENV1	Regulations encourage the use of AI in logistics	0.74	0.88	0.71
	ENV2	AI adoption enhances competitive advantage	0.86		
	ENV3	Customers expect AI-enabled services	0.83		
Task Characteristics (TAS)	TAS1	Logistics tasks require intelligent support	0.72	0.86	0.68
	TAS2	Tasks require coordination across functions	0.83		
	TAS3	Logistics tasks are performed frequently	0.79		
Technology Characteristics (TCH)	TCH1	AI systems meet task requirements	0.76	0.89	0.72
	TCH2	AI tools provide real-time logistics data	0.88		

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	TCH3	AI automates repetitive logistics tasks	0.84		
Task–Technology Fit (TTF)	TTF1	AI features align with logistics tasks	0.79	0.91	0.76
	TTF2	Good match between AI capabilities and task needs	0.90		
	TTF3	AI improves efficiency of logistics tasks	0.87		
Performance Expectancy (PE)	PE1	AI improves efficiency of logistics tasks	0.82	0.92	0.79
	PE2	AI enhances job performance	0.91		
	PE3	AI improves work accuracy	0.88		
Effort Expectancy (EE)	EE1	Learning to operate AI systems is easy	0.74	0.88	0.71
	EE2	AI technologies are user-friendly	0.86		
	EE3	AI systems are easy to use regularly	0.83		
Social Influence (SI)	SI1	Influential individuals support AI adoption	0.76	0.89	0.73
	SI2	Organization expects AI usage	0.87		
	SI3	Managers encourage AI adoption	0.85		
Facilitating Conditions (FC)	FC1	Organization provides sufficient AI resources	0.75	0.90	0.74
	FC2	Organization provides AI training	0.88		
	FC3	AI systems are compatible with infrastructure	0.86		
Behavioral Intention (BI)	BI1	I intend to use AI in logistics tasks	0.83	0.93	0.82
	BI2	I will regularly use AI when available	0.92		
	BI3	I am committed to integrating AI into work	0.90		
AI Adoption (AI)	AI1	Organization currently uses AI systems	0.80	0.91	0.77
	AI2	AI has been used in operations within six months	0.89		
	AI3	AI tools are integrated into logistics processes	0.86		

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