The following publication J. Aslam, A. Saleem and K. -H. Lai, "Supply Chain Management in the Era of Generative AI (ChatGPT): Technology Fit and Psychological Drivers of Adoption," in IEEE Transactions on Engineering Management, vol. 72, pp. 3817-3831, 2025 is available at https://doi.org/10.1109/TEM.2025.3605823.

Supply Chain Management in the Era of Generative AI (ChatGPT): Technology Fit and Psychological Drivers of Adoption

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Abstract:

The rise of generative AI (Gen-AI), particularly ChatGPT, is reshaping the landscape of supply chain management (SCM) by enabling interactive, real-time, and language-based intelligence. Unlike traditional AI systems that operate on structured data and predefined rules, ChatGPT introduces a conversational interface that supports decision-making, problem-solving, and coordination across various SCM functions. This study examines the adoption of ChatGPT by assessing its alignment with four key supply chain tasks: optimization, adaptability, sustainability, and coordination. To explain the mechanisms driving adoption, we integrate the Task-Technology Fit (TTF) theory with the Stimulus-Organism-Response (SOR) framework, modeling ChatGPT as a stimulus that influences user trust, satisfaction, and technology anxiety—cognitive and emotional responses that shape behavioral intention. Empirical data were collected from 382 SCM professionals across diverse industries and analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM). The results demonstrate that perceived task-technology fit significantly enhances trust and satisfaction, both of which have a positive influence on the intention to adopt ChatGPT. Importantly, the study reveals that technology anxiety moderates these relationships, diminishing the strength of trust and satisfaction in driving adoption. This finding highlights the importance of addressing psychological resistance in conjunction with the deployment of technology. By offering a dual-theoretical lens and empirical validation, this research contributes to the emerging literature on Gen-AI adoption, providing actionable insights for practitioners seeking to integrate ChatGPT into their supply chain operations.

Keywords: Generative AI, Gen-AI, ChatGPT, Supply Chain Management, Task Technology Fit, SOR Model.

Managerial relevance statement:

As supply chains grow increasingly complex and digitally interconnected, managers are under pressure to adopt emerging technologies that enhance agility, efficiency, and collaboration. This study offers timely insights into how generative AI (Gen-AI) tools—specifically ChatGPT—can be effectively integrated into supply chain operations. The findings demonstrate that ChatGPT can enhance key supply chain functions, including optimization, sustainability, and coordination, when its capabilities are perceived to align with operational tasks. Managers should therefore focus on evaluating Gen-AI tools not just for their novelty, but also for their suitability in real-world supply chain processes. The research also highlights the critical role of user experience in technology adoption, demonstrating that trust and satisfaction are crucial in driving usage. Importantly, it uncovers that technology anxiety can act as a barrier even among employees who recognize ChatGPT's value. This suggests that successful adoption strategies must include not only technical implementation but also change management, employee training, and psychological support. By addressing both functional alignment and user acceptance, this study offers practical guidance for managers seeking to deploy Gen-AI to improve supply chain performance.

I. INTRODUCTION

Artificial Intelligence (AI) has been a transformative force in reshaping production, operations, and supply chain management (SCM). Traditionally, AI's application in SCM has centered on automating routine tasks and optimizing processes, such as demand forecasting, inventory control, and predictive maintenance, leading to measurable improvements in efficiency and cost reduction [1]. With the evolution of machine learning (ML) and computational power, AI has grown from rule-based systems to more intelligent and adaptive technologies [2].

The recent rise of Generative AI (Gen-AI), particularly conversational tools such as ChatGPT, has introduced a transformative shift in the application of AI within SCM. Unlike traditional AI systems that rely heavily on structured datasets and rule-based logic, Gen-AI offers a more dynamic and interactive approach [3]. ChatGPT, for instance, leverages advanced natural language processing (NLP) to engage in complex, human-like conversations, allowing supply chain professionals to interact with AI in an intuitive and accessible manner. This evolution from static automation to conversational intelligence empowers users to address problems, make decisions, and adapt strategies in real-time, without requiring technical expertise or programming skills [4]. Within the SCM context, ChatGPT enhances decision-making by providing real-time insights, facilitating seamless communication, and supporting cross-functional stakeholder collaboration [5].

Prior studies have begun exploring the benefits of Gen-AI in supply chain (SC), with early research highlighting the potential for improved decision-making, enhanced automation, and increased sustainability [6]. For instance, Li *et al.* [7] examined how Gen-AI can be applied to promote green SC collaboration and circular economy practices, demonstrating its role in improving sustainable SC performance by fostering collaboration and reducing environmental impact. Similarly, Haddud [3] identified potential applications of ChatGPT in SC, ranging from demand forecasting to supplier management, and emphasized the benefits of improved process efficiency, enhanced customer satisfaction, and cost reduction. Wamba *et al.* [8] examined the impact of ChatGPT on operations and SCM by automating routine tasks, optimizing logistics, and improving risk management.

Despite these valuable contributions, several critical gaps remain. While previous studies have established the conceptual groundwork for ChatGPT's role in SCM, most have focused on theoretical or descriptive applications and proof-of-concept projects [3], [5], [8], [9]. The empirical evidence on how ChatGPT can be effectively implemented at a broader scale is still scarce. Furthermore, although existing research identifies the operational benefits of ChatGPT, there has been limited attention to the organizational, technological, and human-centered challenges that could hinder its adoption, such as user trust, satisfaction, and technology anxiety. Prior studies acknowledge that the practical implications of Gen-AI capabilities for decision-making and cross-industry applications require further exploration [10].

Despite the growing attention to ChatGPT, a significant gap remains in understanding how these tools can be effectively integrated into SCM. The study extends the current literature by providing a comprehensive analysis of ChatGPT's capabilities and its role in enhancing SCM operations in areas such as optimization, adaptability, sustainability, and coordination. Furthermore, the adoption of ChatGPT in SC remains relatively slow. Various factors drive this reluctance, including technology anxiety, where employees are apprehensive about the complexities of AI systems, and a fear of losing their jobs. Trust is another significant obstacle—users might doubt the dependability and precision of AI-generated insights, especially in an SC environment. Additionally, user satisfaction with AI tools often depends on their usability and the perceived benefits they offer in daily tasks. As SC becomes increasingly intricate and digitized, the demand for AI systems that can engage with human users naturally and seamlessly is crucial. Furthermore, there is a lack of research regarding the human-centric obstacles to adopting Gen-AI, including how technology anxiety can inhibit trust and satisfaction, which are crucial for organizational uptake. Thus, this study raises the following research questions;

RQ1: To what extent is Gen-AI (ChatGPT) aligned with key supply chain tasks such as optimization, adaptability, sustainability, and coordination for effective integration into SCM?

RQ2: How do technology anxiety, trust, and satisfaction influence employees' intention to adopt Gen-AI (ChatGPT) in SCM?

This study addresses these questions by examining the Task-Technology Fit (TTF) of ChatGPT, ensuring it aligns with critical SC tasks such as optimization, adaptability, sustainability, and coordination. Additionally, the Stimulus-Organism-Response (SOR) framework helps to understand how ChatGPT's capabilities for SCM influence employee trust and satisfaction towards adopting ChatGPT at the firm level. This study also examines human-centered challenges, including how technology anxiety impacts trust, satisfaction, and the adoption of ChatGPT. Using the TTF model and the SOR framework, this research assesses the alignment of ChatGPT with SC tasks and offers a nuanced understanding of the psychological and behavioral factors influencing its adoption. To advance understanding of ChatGPT adoption in SC contexts, this study examines not only the direct impact of TTF on adoption intention but also the psychological mechanisms that underlie this relationship. Drawing on the SOR framework, the study explores how trust and satisfaction serve as mediators that translate perceived task alignment into behavioral intention. Additionally, the study considers technology anxiety as a moderating factor that may weaken the influence of trust and satisfaction, recognizing that emotional responses to ChatGPT can complicate otherwise favorable adoption conditions.

The structure of the paper is organized as follows: Section 2 presents the underlying theories, develops hypotheses, and the conceptual model. Section 3 outlines the methodology used in the study. Section 4 presents an in-depth analysis of the results. Section 5 discusses the study's practical and theoretical implications. Finally, Section 6 concludes the paper by summarizing the key findings, addressing the study's limitations, and offering recommendations for future research.

II. UNDERLYING THEORIES AND HYPOTHESES DEVELOPMENT, AND CONCEPTUAL MODEL

ChatGPT, developed by OpenAI, represents a class of Gen-AI systems that utilize large language models (LLMs) to generate human-like text in real-time. Unlike traditional AI tools that are rule-based or domain-specific, ChatGPT operates with a high degree of flexibility, enabling users to interact with it conversationally, iteratively, and intuitively. Its ability to generate, synthesize, and contextualize content has positioned it as a powerful tool across a range of applications, including writing assistance, knowledge search, content summarization, problem-solving, and decision support [11]. In the context of SCM, ChatGPT offers several potential capabilities that can support both operational and strategic functions. For instance, it can facilitate real-time communication across internal teams and external partners, assist in demand forecasting through data summarization, support sustainability reporting, and enhance coordination and training through accessible, AI-driven guidance [5]. Its language-based interface also reduces the technical barrier to AI adoption, enabling non-technical users to engage more effectively with advanced analytics and decision-making tools.

Moreover, ChatGPT's interactive nature allows users to ask follow-up questions, clarify ambiguities, and refine outputs [12]—features that align well with the dynamic needs of SC professionals. These affordances make ChatGPT not only a functional tool but also a collaborative digital assistant capable of supporting complex, high-context decisions. However, its integration into SCM also raises questions around trust, reliability, transparency, and user comfort, especially in data-sensitive or high-risk operational settings. Given these characteristics, ChatGPT is a compelling test case for evaluating both task-technology fit and user-centric psychological responses—two pillars central to understanding its adoption in organizational contexts. This study, therefore, investigates how ChatGPT's perceived capabilities align with SC tasks and how users' trust, satisfaction, and technology-related anxiety influence their intention to adopt the tool.

A. Supply Chain Tasks and ChatGPT as Task Technology Fit

TTF theory provides a foundational framework for understanding the effectiveness of technology in organizational contexts [13]. TTF posits that the successful adoption and performance of technology depend on the degree to which it fits the tasks it intends to support [14]. In essence, if the capabilities of a technology are well-aligned with the requirements of the tasks, the technology is more likely to enhance user performance and lead to higher utilization levels [15]. At its core, TTF theory emphasizes the interplay between the task characteristics (the specific work or process being carried out), the technology characteristics (the features and functionalities of the technology), and the individual's ability to use the technology effectively [16], [17].

The TTF framework can also provide insights into adopting ChatGPT in SCM by focusing on the task and technology fit for operational and strategic tasks. For instance, for ChatGPT to be effective in supply chains, it must be capable of handling tasks such as real-time information, automated decision-making, and generating insights from large volumes of data. Moreover, the TTF theory suggests that beyond the technology's inherent capabilities, SC professionals' perception of fit is crucial. Suppose users perceive that ChatGPT does not adequately support their tasks—whether due to limitations in data interpretation, response accuracy, or other factors—its adoption will likely be hindered, regardless of its potential advantages [18]. This study identified the four critical SC tasks, such as optimization, adaptability, sustainability, and coordination [19], [20], [21], [22], [23], and analyzed the role of ChatGPT as TTF in the context of SCM.

In SCM, optimization involves improving efficiency, reducing costs, and enhancing decision-making processes across demand forecasting, inventory management, and logistics planning tasks [24]. ChatGPT plays a crucial role in optimization by offering advanced capabilities, including real-time data analysis, automated decision-making, and predictive insights. When ChatGPT is integrated into SC, it helps streamline operations by delivering faster, more accurate responses to complex tasks, allowing SC professionals to optimize resources and improve overall performance [25], [26]. Consequently, TTF theory suggests that the better a technology supports the specific tasks required in an organization, the more likely it is to improve user performance and satisfaction [27]. In the case of Gen-AI-driven SC optimization, ChatGPT's ability to enhance real-time decision-making and improve operational efficiency directly aligns with the core tasks of SCM. Thus, the study proposed the following hypothesis.

H_1: Gen-AI (ChatGPT)-driven SC optimization is positively correlated with TTF.

In the SC context, adaptability refers to a firm's ability to handle disruptions, such as natural disasters, geopolitical events, or unexpected shifts in demand, that can significantly impact operations [28]. Managing these disruptions requires real-time responses, rapid decision-making, and the ability to adjust plans quickly [29]. ChatGPT offers advanced tools to manage uncertainties by providing predictive insights, automated risk assessments, and real-time communication capabilities [30], which supports SC adaptability. Referring to TTF, ChatGPT functionalities allow SC to respond to market changes more efficiently and effectively, minimizing negative impacts and ensuring continuity [31]. The strong fit between ChatGPT's capabilities and SC adaptability leads to more effective performance and identifies a better alignment between SC and technology characteristics; thus, this study proposes the following hypothesis.

H_2: Gen-AI (ChatGPT)-driven SC adaptability is positively related to TTF.

As sustainability becomes a key focus in SCM, organizations increasingly seek ways to reduce their environmental footprint, optimize resource use, and meet regulatory demands [32]. ChatGPT offers valuable support in these efforts by providing sustainability monitoring tools, tracking carbon footprint, and optimizing resources [33]. By analyzing large datasets, ChatGPT can offer actionable insights into energy use, waste management, and sustainable sourcing, helping companies align their SC activities with sustainability goals [34]. TTF theory emphasizes that technology is most effective when its capabilities match the specific tasks it is designed to support.

In the context of SC sustainability, ChatGPT's ability to generate sustainability reports, track real-time data on emissions, and suggest greener alternatives [35] makes it highly relevant to the tasks associated with building a more sustainable SC. When ChatGPT's features align well with sustainability-focused tasks, it enhances the efficiency of SC processes; thus, this study proposes the following hypotheses.

H_3: Gen-AI (ChatGPT)-driven SC sustainability is positively related to TTF.

Coordination is essential to successful SCM, especially in complex, globalized networks where multiple stakeholders, suppliers, and teams must coordinate in real-time [36]. ChatGPT enhances these aspects by offering real-time communication, automated responses, and data-driven insights, facilitating better collaboration across teams and suppliers [37]. Therefore, ChatGPT, like TTF, plays a significant role in SC coordination by providing instant responses, automating the integration between internal and external stakeholders, and ensuring a seamless flow of information, all of which are critical to SC coordination. When ChatGPT's capabilities effectively support these coordination tasks, the result is a stronger TTF, leading to enhanced task performance. Thus, the study proposes the following hypothesis.

H_4: Gen-AI (ChatGPT)-driven SC coordination is positively related to TTF.

B. Stimulus-Organism-Response (SOR) framework and ChatGPT adoption

The SOR framework provides a comprehensive approach to understanding how external stimuli influence individual behaviors by affecting cognitive and emotional states [38]. The SOR framework consists of three key components: *Stimulus (S), Organism (O), and Response (R),* which together explain the behavioral responses individuals exhibit when exposed to external environmental factors [39]. In the context of this study, the *Stimulus (S)* represents the introduction of ChatGPT as a technological tool within SCM. ChatGPT, as an external stimulus, offers unique capabilities such as SC optimization, adaptability, sustainability, and coordination. For this aspect, this study analyzes the SC task and ChatGPT capabilities using the TTF theory. The *Organism (O)* in this framework refers to the internal cognitive and emotional reactions of SC professionals or employees as they engage with ChatGPT. These internal states encompass trust in the technology's capabilities, satisfaction with its performance [40], and feelings of technology anxiety or apprehension toward adoption [41]. The *Response (R)*, the final stage in the SOR framework, refers to the behavioral outcomes resulting from the interaction between the stimulus and the organism [42]. These responses can manifest as positive behaviors, such as the intention to adopt ChatGPT within SCM, or negative behaviors, including resistance to adoption or reliance on traditional systems due to a lack of trust, dissatisfaction, and technology anxiety [43].

Ultimately, the SOR framework suggests that users' cognitive evaluations of ChatGPT, such as whether it aligns well with the tasks they need to perform based on the TTF, and their emotional responses, including whether they feel comfortable using ChatGPT. For example, an SC manager or employee who feels confident in ChatGPT's ability to optimize SC tasks may experience high satisfaction and build trust, whereas another user, anxious about ChatGPT's potential mistakes, may hesitate to fully adopt the technology.

According to the proposed study, ChatGPT, as TTF, serves as the external stimulus (S) in the SOR model, where its fit with SC influences users' trust and satisfaction with the *organism (O)*. A higher degree of TTF—where ChatGPT efficiently supports SC tasks such as optimization, adaptability, sustainability, and coordination—elicits a positive cognitive response in users, leading to increased trust and satisfaction in the tool's ability to perform accurately and reliably. Trust and satisfaction are essential for adoption and reliance on ChatGPT within SC operations. The stronger the alignment between TTF functionalities, the stronger the user trust, which in turn fosters greater satisfaction with the technology [44]. Thus, this study proposed the following hypotheses.

H_5: ChatGPT as TTF is positively related to trust in ChatGPT.

H_6: ChatGPT as TTF is positively related to satisfaction in ChatGPT.

Trust in ChatGPT refers to the employee's belief that the technology is reliable, accurate, and capable of effectively supporting SC tasks. When employees trust that ChatGPT can consistently deliver correct and valuable insights, they are more likely to integrate it into their daily workflows and rely on it for key operations [45]. Furthermore, in the context of technology adoption, user satisfaction plays a crucial role in determining whether individuals continue to use and fully integrate technology into their workflows [46]. Satisfaction reflects the user's positive evaluation of the technology's ability to meet or exceed expectations [47]. In the context of ChatGPT, when users perceive that the tool effectively supports supply chain tasks and provides meaningful value, they are likely to experience satisfaction, which subsequently increases their willingness to adopt the technology [48].

According to the SOR model, trust and satisfaction in ChatGPT serve as an internal *organism (O)* state, shaped by external factors (e.g., the technology's performance). Trust and satisfaction influence the *response (R),* which is the intention to adopt ChatGPT within SC processes. Higher levels of trust reduce concerns about the technology's accuracy and performance, making users more confident in adopting it for long-term use in SCM. Similarly, higher levels of satisfaction reinforce a user's confidence in the technology [49], making it more likely to integrate ChatGPT into their daily operations and recommend its use across the organization. Moreover, it is essential to determine whether the perceived fit itself directly influences behavioral intention. TTF theory posits that when users perceive a strong alignment between the capabilities of a technology and the requirements of their tasks, they are more likely to adopt that technology. In this context, if ChatGPT is seen as well-suited to support decision-making, problem-solving, or coordination, users may be more inclined to integrate it into their professional workflows. Thus, the study proposes the following hypotheses.

H_7: Trust in ChatGPT is positively related to the intention to adopt ChatGPT.

H_8: Satisfaction with ChatGPT is positively related to the intention to adopt ChatGPT.

H_9: ChatGPT as TTF is positively related to the intention to adopt ChatGPT.

While trust and satisfaction are each expected to directly influence the intention to adopt ChatGPT (H_7 and H_8), it is also important to examine whether these psychological states act as underlying mechanisms through which TTF influences adoption behavior. A high degree of perceived TTF gives rise to positive psychological responses that encourage behavioral commitment. In this regard, trust and satisfaction can be viewed as mediators that explain how and why functional alignment with ChatGPT's capabilities leads to adoption intention. When users perceive that ChatGPT effectively supports SC tasks, this perception enhances their trust in the system's reliability and increases satisfaction with its usefulness. These responses, in turn, drive the intention to adopt [50], [51]. In line with the SOR framework, TTF acts as an external stimulus that shapes internal organismic responses, including satisfaction, which subsequently influence behavioral responses such as the intention to adopt the technology. Prior research supports this conceptualization, suggesting that satisfaction can emerge from initial perceptions of usefulness and task alignment, even in early stages of technology interaction [48], [52], [53]. In this context, a high degree of perceived TTF enhances users' satisfaction by signaling that the technology can help them perform their work more effectively and efficiently. This positive emotional response, in turn, motivates users toward adoption. Accordingly, satisfaction and trust serve as a psychological mechanism through which perceived TTF is translated into adoption intention. Accordingly, the following hypotheses are proposed:

H_{9a}: Trust mediates the relationship between TTF and intention to adopt ChatGPT.

H_{9b}: Satisfaction mediates the relationship between TTF and intention to adopt ChatGPT.

C. Technology anxiety and ChatGPT adoption

Technology anxiety refers to the fear, apprehension, or discomfort that users may experience when interacting with new or advanced technologies [54]. This anxiety can arise from concerns about the complexity of the tool, fear of making mistakes, job displacement, or uncertainty about the technology's accuracy and reliability. In the context of new technology adoption, users' trust and satisfaction in technology are paramount; technology anxiety can significantly impact the adoption of AI-driven tools such as ChatGPT [55]. Trust plays a critical role in technology adoption—users are more likely to adopt ChatGPT if they trust its capabilities. However, when users experience high levels of technology anxiety, it can negatively affect this relationship [56]. Even if they trust ChatGPT, their anxiety may cause hesitation or reluctance to adopt the tool, as seen in previous research. [41], [57].

Similarly, satisfaction with ChatGPT—arising from its ability to enhance task performance and ease of use—generally increases users' intention to adopt the Gen-AI [58]. However, technology anxiety can also weaken this relationship [59]. Even when users are satisfied with ChatGPT's functionality, their anxiety about interacting with the technology may reduce their willingness to adopt it. This indicates that technology anxiety not only influences trust but also diminishes the effect of satisfaction on the decision to adopt ChatGPT [60] within SC operations. Based on this, the study proposes the following hypotheses.

H_{10a}: Technology anxiety moderates the relationship between trust in ChatGPT and intention to adopt ChatGPT.

H_{10b}: Technology anxiety moderates the relationship between satisfaction with ChatGPT and intention to adopt ChatGPT.

D. Conceptual model

The proposed model of this research is an integration of the TTF theory and the SOR framework. TTF represents the alignment between ChatGPT's capabilities and the specific tasks within SC, including optimization, adaptability, sustainability, and coordination. The SOR model explains how this fit influences users' internal cognitive responses (trust and satisfaction) and emotional responses (intention to adopt ChatGPT). Furthermore, this study proposes that technology anxiety serves as a moderator, influencing the relationship between trust and satisfaction, and ultimately the intention to adopt ChatGPT.

The SOR framework offers a versatile structure for examining how external stimuli evoke internal psychological states that drive behavioral outcomes. It is particularly well-suited for studying emerging technologies, where users' initial cognitive and emotional reactions often play a central role in shaping their behavioral intentions. In this study, the SOR framework is used to model how users respond to ChatGPT's perceived fit with SC tasks. The organismic states—trust, satisfaction, and technology anxiety—capture users' early appraisals formed through professional exposure to the tool. These appraisals serve as the basis for the response: the intention to adopt ChatGPT within SC operations. Building on the SOR framework, this study examines not only the direct influence of TTF on the intention to adopt ChatGPT but also explores how psychological mechanisms such as trust and satisfaction mediate this relationship. Moreover, the study also examines technology anxiety as a moderating factor that may weaken the influence of trust and satisfaction on adoption intention. Given the complexity of ChatGPT, anxiety may act as a psychological barrier, even when users perceive a strong task fit. Fig. 1 presents the research model and proposed hypotheses of the proposed study.

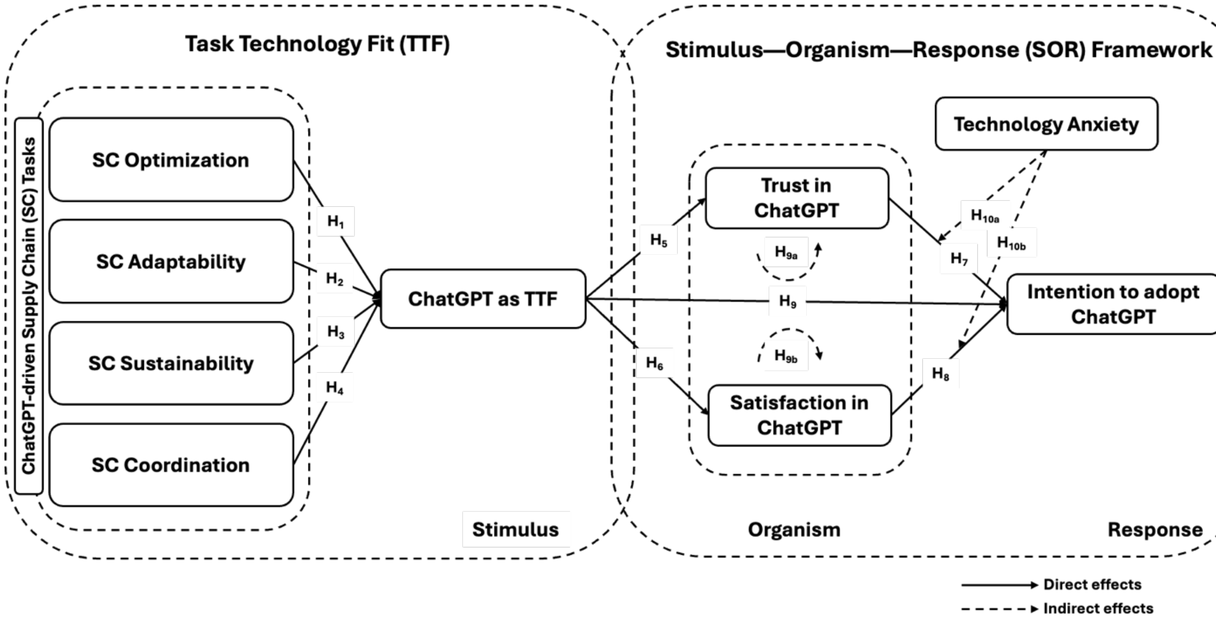

Fig. 1. Research Model

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III. METHODS

A. Data collection

The methodology of this study focuses on understanding the perceptions of SC professionals and employees across diverse industries regarding the adoption of generative AI tools—specifically ChatGPT—to enhance various SC tasks. To collect the necessary data, we designed a structured survey and distributed it using a combination of professional networking platforms (e.g., LinkedIn, ResearchGate) and industry-specific forums (e.g., Global Supply Chain Institute (GSCI), Association of Supply Chain Management (ASCM), Institute of Supply Chain Management (ISM), and groups focused on SC and operations management. The survey targeted individuals currently working in roles related to logistics, procurement, production planning, SC analytics, or operations strategy. To ensure participant relevance, a screening question was used to confirm that respondents had at least basic familiarity with ChatGPT. Additionally, Table I presents demographic and industry diversity across regions, designations, experience, qualifications, and sectors, as part of the respondent profile. A survey was distributed among 550 professionals, aiming for broad representation across industries, regions, and organizational roles. Of these, 405 responses were received, and after 23 incomplete or invalid responses were removed, 382 valid responses were retained for final analysis, resulting in an effective response rate of 69%.

B. Measures and questionnaire development

We developed the survey questionnaire, ensuring it was reliable and relevant to the study's objectives. The constructs used in this study were measured using validated scales from previous research, with modifications made to tailor the items to the specific context of this research (Appendix A). This study focused on nine constructs, which included independent, dependent, and moderating variables, all measured on a 5-point Likert scale, ranging from 1 (strongly disagree) to 5 (strongly agree). The ChatGPT-driven SC tasks were consistent with the four key dimensions: optimization, adaptability, sustainability, and coordination. Haddud [3] developed a structured questionnaire to evaluate ChatGPT's potential benefits across 15 supply chain areas using a 5-point Likert scale. These areas included process efficiency, demand forecasting, sustainability reporting, supplier communication, and logistics optimization—domains conceptually aligned with key SC capabilities. Building on this foundation, we adapted and organized these application areas into four broader supply chain task dimensions—optimization, adaptability, sustainability, and coordination. SC optimization was measured using a seven-item scale adapted from Haddud [3]. SC adaptability was evaluated using a four-item scale [3], [61]. SC sustainability was measured using a four-item scale [3], [62]. SC coordination was assessed using a four-item scale [3]. A three-item scale was used and adapted for the TTF construct related to ChatGPT [14], [63]. Trust in ChatGPT was measured using a four-item scale [64], while satisfaction with ChatGPT was measured with a four-item scale [48]. Technology anxiety was captured using a three-item [65]. Lastly, the intention to adopt ChatGPT was measured with a three-item scale [66]. Regarding demographic information about SC employees, the survey included one screening question (to assess ChatGPT's understanding) and five questions covering key respondent attributes, including industry type, region, designation, qualification, and years of experience.

IV. RESULTS

A. Demographic analysis

The demographic profile of the respondents provides a broad and diverse representation across industry types, regions, designations, qualifications, and experience levels. Table I presents the profile of respondents.

Table I. Respondent Profile

Demographic Questions		Frequency	Percentage
ChatGPT understanding	Yes	382	100
(screening question)	No	0	0
Industry type	Tech and Electronics	65	17.1
	e-commerce	90	23.6
	Retail	75	19.6
	Food and Beverages	60	15.7
	Automotive	52	13.6
	Pharmacetical	40	10.4
Region	United State	72	18.9
	China	130	34.0
	India	81	21.2
	Europe	58	15.1
	South Korea	41	10.7
Designation	SC Analyst	86	22.5
	SC Strategist	45	11.8
	SC Officer	105	27.5
	SC Manager	45	11.8
	Logistics Manager	49	12.8
	Assistant Manager SC	52	13.6

Qualification	Diploma	40	10.4
	Undergraduate	83	21.7
	Master	128	33.6
	PhD	70	18.4
	Certification	61	15.9
Experience (Years)	5-10	45	11.8
	11-15	191	50.0
	16-20	105	27.5
	Above 20	41	10.7

B. Common method bias

In this study, two methods were employed to assess common method variance (CMV) formally. First, Exploratory Factor Analysis (EFA) using Harman's one-factor test was conducted. The results showed that no single factor accounted for most of the variance, indicating that CMV was not a significant issue [67]. Second, the Variance Inflation Factor (VIF) was examined using PLS-SEM. A VIF above 3.3 suggests collinearity and potential bias; however, Table II revealed that all VIF values were below 3.3, further confirming that collinearity and common method bias were not concerns in this study.

C. Reliability and validity analysis

Table II presents the Cronbach's alpha (α) values, ranging from 0.769 to 0.970, indicating strong reliability for all constructs. Additionally, the composite reliability (CR) for each item, ranging from 0.919 to 0.982, exceeds the recommended threshold of 0.70, supporting the internal consistency of the constructs [68]. The factor loadings for all constructs are statistically significant, with coefficients greater than 0.769, further affirming the constructs' reliability and validity. Moreover, the average variance extracted (AVE) was calculated to assess convergent validity. The AVE values for all constructs exceeded 0.739, well above the accepted threshold of 0.5, indicating that their respective constructs capture a substantial portion of the variance in the indicators.

Table II. Reliability and Validity

Variable	Items	Factor Loading	α	CR	AVE	VIF
SC optimization (OPT)	OPT1	0.934	0.977	0.980	0.877	2.885
	OPT2	0.939				2.013
	OPT3	0.933				1.929
	OPT4	0.942				2.242

	OPT5	0.940				2.429
	OPT6	0.945				1.562
	OPT7	0.922				1.750
SC adaptability	ADP1	0.930	0.899	0.930	0.770	3.201
(ADP)	ADP2	0.918				3.122
	ADP3	0.857				2.539
	ADP4	0.799				1.775
SC	SUS1	0.876	0.892	0.926	0.758	2.649
sustainbility	SUS2	0.922				2.438
(SUS)	SUS3	0.908				2.823
	SUS4	0.769				1.592
SC	COD1	0.769	0.901	0.932	0.776	1.590
coordination	COD2	0.907				3.104
(COD)	COD3	0.937				2.901
	COD4	0.900				3.201
Task	TTF1	0.970	0.973	0.982	0.948	2.494
technology fit	TTF2	0.983				2.975
(TTF)	TTF3	0.968				1.930
Trust (TRT)	TRT1	0.946	0.941	0.959	0.853	2.236
	TRT2	0.962				2.411
	TRT3	0.962				2.678
	TRT4	0.816				2.007
Satisfaction	STF1	0.897	0.833	0.919	0.739	2.057
(STF)	STF2	0.858				2.666
	STF3	0.843				2.767
	STF4	0.839				2.717
Technology	TEA1	0.966	0.959	0.973	0.924	2.139
Anxiety (TEA)	TEA2	0.965				2.942
	TEA3	0.953				2.911
Intention to	INT1	0.947	0.945	0.965	0.901	2.441
adopt ChatGPT	INT2	0.948				2.556
(INT)	INT3	0.953				1.906

D. Correlations and discriminant validity

To assess the discriminant validity of the constructs, the study compared the square root of the AVE with the correlations between the constructs. This comparison helps determine whether each construct is distinct from the others. Additionally, the heterotrait-monotrait ratio (HTMT) was used to verify discriminant validity further. Table III showed that all HTMT values were below the recommended threshold of 0.85, indicating strong evidence of discriminant validity among the constructs. Furthermore, the square root of the AVE for each construct, displayed along the diagonal (bold and italic) in the correlation matrix (Table III), was consistently higher than the correlations with other constructs.

Table III. HTMT of the Correlation and Discriminant Validity

	OPT	DIS	SUS	COM	TTF	TRT	STF	TEA	INT
OPT	***0.936***								
ADP	0.712	***0.877***							
SUS	0.260	0.309	***0.870***						
COM	0.725	0.788	0.271	***0.880***					
TTF	0.617	0.576	0.375	0.664	***0.973***				
TRT	0.633	0.609	0.370	0.742	0.436	***0.923***			
STF	0.661	0.647	0.337	0.774	0.557	0.604	***0.859***		
TEA	0.608	0.578	0.373	0.683	0.749	0.782	0.592	***0.961***	
INT	0.712	0.709	0.264	0.712	0.597	0.605	0.610	0.591	***0.949***

E. Hypothesis testing

Using SMART-PLS 4.0 software, the study examines the direct and moderating relationships between the variables, following the structure of its conceptual framework (Fig. 1).

A. Direct effects

The results indicate that H_1 was supported ($\beta = 0.287$, $p < 0.05$), suggesting that ChatGPT can enhance SC optimization, which aligns well with the tasks, thereby improving its perceived fit. Conversely, H_2 was not supported ($\beta = 0.065$, $p > 0.05$), indicating that SC adaptability is not significantly affected by the introduction of ChatGPT. H_3 was supported ($\beta = 0.180$, $p < 0.05$), indicating that ChatGPT-driven sustainability has a positive impact on TTF. This highlights that using ChatGPT to enhance sustainability practices is well-aligned with the tasks in SC, improving the fit between technology and task requirements. H_4 was also supported ($\beta = 0.337$, $p < 0.05$), showing that SC coordination through ChatGPT has a strong, positive effect on TTF. This suggests that ChatGPT's role in facilitating coordination significantly enhances its alignment with SC, making it highly effective for this purpose.

The results show that H_5 was supported ($\beta = 0.315$, $p < 0.05$), indicating that ChatGPT fits well with SC tasks, as it significantly enhances users' trust, reinforcing the perception that ChatGPT can reliably support SC operations. Similarly, H_6 was supported ($\beta = 0.518$, $p < 0.05$), revealing that ChatGPT aligns well with the tasks it supports, and users are more satisfied with its performance. Regarding the relationship between trust and the intention to adopt ChatGPT, H_7 was not supported ($\beta = 0.159$, $p > 0.05$), indicating that SC employees may have trust issues with ChatGPT, which affects their decision to adopt. H_8 was supported ($\beta = 0.358$, $p < 0.05$), demonstrating that when users are satisfied with ChatGPT's ability to perform tasks effectively, they are more likely to adopt the Gen-AI. Finally, H_9 was found to be statistically significant ($\beta = 0.304$, $p < 0.05$), indicating that users who perceive a strong alignment between ChatGPT's capabilities and their task requirements are more likely to adopt the tool. This finding highlights the importance of functional relevance in adoption decisions: when users believe that ChatGPT effectively supports SC activities, they are more motivated to adopt it into their tasks. Table IV presents the direct relationship of the proposed hypotheses from H_1 to H_9.

Table IV. Direct relationship of proposed hypotheses

	Path	**Beta**	**Sample Mean**	**STDEV**	**T-value**	**p-value**	**R^2**
H_1	SC Optimization → TTF	0.287	0.287	0.064	4.459	0.000	0.480
H_2	SC Adaptability → TTF	0.065	0.066	0.058	1.131	0.258	
H_3	SC Sustainability → TTF	0.180	0.181	0.038	4.737	0.000	
H_4	SC Coordination → TTF	0.337	0.337	0.062	5.446	0.000	
H_5	TTF → Trust	0.315	0.316	0.060	5.895	0.000	0.538
H_6	TTF → Satisfaction	0.518	0.519	0.050	10.273	0.000	0.268
H_7	Trust → Intention to adopt ChatGPT	0.159	0.516	0.114	1.387	0.166	0.495
H_8	Satisfaction → Intention to adopt ChatGPT	0.358	0.361	0.057	6.241	0.000	
H_9	TTF → Intention to adopt ChatGPT	0.304	0.300	0.126	2.409	0.016	

B. Mediating effects

The mediation analysis reveals contrasting effects of trust and satisfaction in the pathway between TTF and intention to adopt ChatGPT. For H_{9a}, the indirect effect of TTF on intention to adopt ChatGPT through trust was not statistically significant ($\beta = 0.020$, $p = 0.875$), indicating that trust does not serve as a meaningful mediator in this relationship. This suggests that while TTF may influence users' trust in the technology, this trust alone does not translate into a higher likelihood of adoption. In contrast, H_{9b} was strongly supported: the indirect effect of TTF on adoption intention through satisfaction was significant and positive ($\beta = 0.186$, $p < 0.001$). This finding confirms that satisfaction is a key mediating mechanism through which perceptions of task alignment are converted into behavioral intention. In other words, when users feel that ChatGPT effectively supports their SC tasks, it enhances their satisfaction with the tool, which in turn increases their motivation to adopt it. This underscores the importance of designing Gen-AI tools that not only fit users' functional needs but also create a positive user experience that reinforces adoption decisions. Table V presents the mediation result of H_{9a} and H_{9b}.

Table V. Mediating effects

Path		Beta	Sample Mean	STDEV	T-value	p-value
H_{9a}	TTF → Trust → Intention to adopt ChatGPT	0.020	0.018	0.126	0.157	0.875
H_{9b}	TTF → Satisfaction → Intention to adopt ChatGPT	0.186	0.188	0.036	5.087	0.000

C. Moderating effects

The results provide support for both H_{10a} and H_{10b}, confirming that technology anxiety moderates the relationship between psychological evaluations and adoption intention. Specifically, the interaction between technology anxiety and trust has a significant negative effect on the intention to adopt ChatGPT ($\beta = -0.096$, $p = 0.015$). This suggests that while trust generally promotes adoption, its positive influence diminishes when users experience higher levels of anxiety. In such cases, even if individuals trust the technology's capabilities, their apprehension about complexity, loss of control, or potential errors can suppress their willingness to adopt it. Similarly, the moderating effect of technology anxiety on the relationship between satisfaction and adoption intention is both negative and statistically stronger ($\beta = -0.251$, $p < 0.001$). This finding implies that satisfaction alone may not be sufficient to ensure adoption if users simultaneously experience anxiety or discomfort with the tool. These results underscore the importance of managing emotional barriers such as anxiety, as they can significantly weaken the impact of otherwise positive evaluations on behavioral intentions. Organizations aiming to implement ChatGPT in SC operations should therefore consider strategies that build user confidence and reduce anxiety to fully leverage the benefits of trust and satisfaction in driving adoption. Table VI presents the results of the moderating hypotheses. Fig. 2 presents the PLS-SEM diagram, including factor loadings, path coefficients, and p-values.

Table VI. Moderating effects

	Path	Beta	Sample Mean	STDEV	T-value	p-value
H_{10a}	(Technology Anxiety X Trust) → Intention to adopt ChatGPT	-0.096	0.095	0.039	2.432	0.015
H_{10b}	(Technology Anxiety X Satisfaction) → Intention to adopt ChatGPT	-0.251	0.249	0.039	6.461	0.000

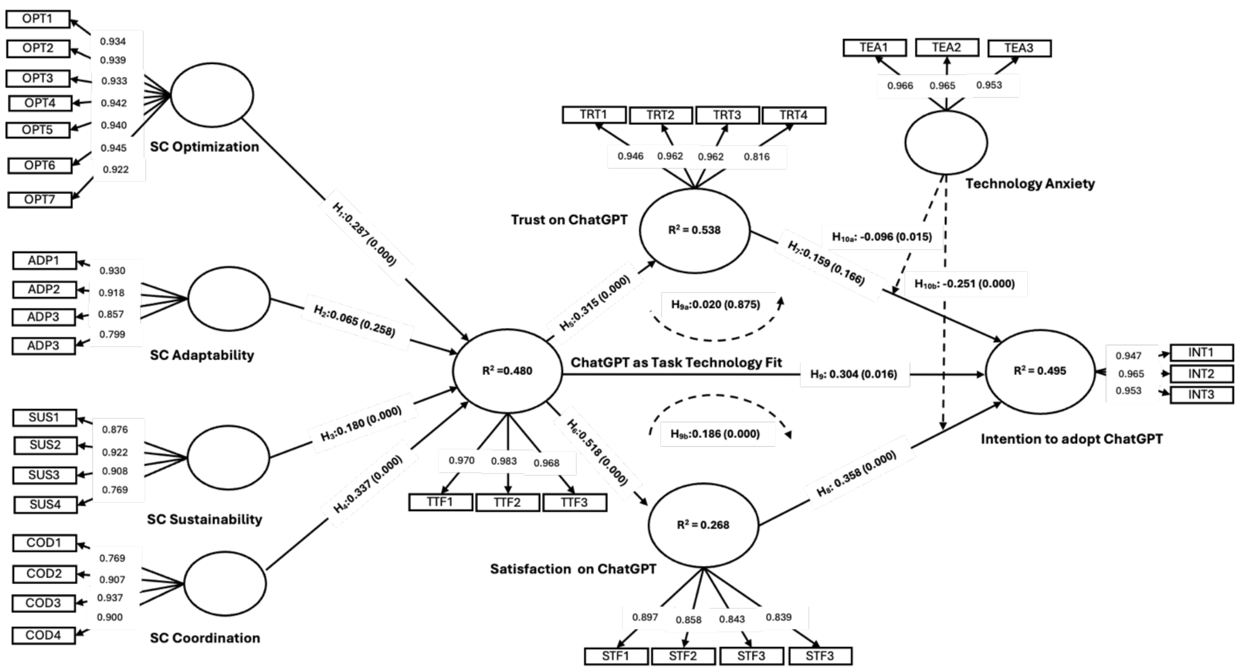

Fig. 2. PLS-SEM result of the model

V. DISCUSSION

This study investigates the adoption of ChatGPT in SCM by integrating TTF theory and the SOR framework. This study makes several important contributions. First, it extends the TTF theory by demonstrating its applicability to Gen-AI in SCM, highlighting the role of ChatGPT in improving SC task performance. Second, integrating the SOR framework helps explain how users' internal cognitive and emotional states—such as trust, satisfaction, and anxiety—influence their behavioral responses to Gen-AI adoption. Third, the study emphasizes the importance of managing technology anxiety to enhance the effectiveness of AI technologies in SCM, thereby contributing to the growing body of literature on the psychological aspects of AI adoption.

The study highlights that optimization, sustainability, and coordination are key drivers of TTF when adopting ChatGPT in SCM. These findings are consistent with emerging real-world applications. For instance, Amazon has integrated LLMs to support demand forecasting and inventory planning [69], and Tesla leverages AI tools for logistics coordination and real-time production optimization [70]. On the sustainability front, companies like Unilever and IKEA have implemented AI technologies to monitor carbon emissions, improve resource utilization, and support ESG compliance [71], [72]. These practices reflect the increasing importance of sustainability in SCM, aligning with our finding that sustainability contributes to perceived TTF. In the area of coordination, Pfizer has used Gen-AI to assist with regulatory documentation and internal process communication [73], [74]. Similarly, DHL has deployed Gen-AI to improve customer service responsiveness and support real-time logistics coordination [75]. Collectively, these examples reinforce the practical relevance of the study's results and illustrate how organizations are beginning to integrate Gen-AI (ChatGPT) into core SCM functions.

The results revealed that the effect of ChatGPT's perceived adaptability on TTF was not significant. This finding is noteworthy, particularly given that adaptability is widely regarded as a critical capability in SCM, where environments are often dynamic, complex, and uncertain. ChatGPT excels in generating structured outputs and responding to clearly framed queries; its current limitations in interactive learning, multi-turn coherence, and situational awareness may constrain its perceived usefulness in highly adaptive SCM scenarios. These might include managing disruptions, responding to ambiguous supplier issues, or improvising under volatile demand conditions—tasks that require fluid interpretation, judgment, and context-specific reasoning. As such, employees may see ChatGPT as more suited for structured, knowledge-based support rather than agile decision-making.

The results revealed that the relationship between ChatGPT as a TTF and the intention to adopt ChatGPT is significant. This confirms that when users perceive ChatGPT as well-aligned with their supply chain tasks, they are more inclined to adopt it into their professional routines. The significance of this relationship underscores the importance of functional relevance in shaping adoption behavior: users are not simply influenced by the novelty of the technology but by its practical value in helping them accomplish their work more efficiently and effectively. This finding supports the theoretical assumption of the TTF model and offers empirical validation in the context of Gen-AI.

The mediation findings offer deeper insights into the psychological mechanisms through which TTF influences the intention to adopt ChatGPT in SC contexts. While both trust and satisfaction are shaped by users’ perceptions of how well ChatGPT aligns with their tasks, only satisfaction serves as an effective channel that converts perceived fit into adoption intention. This suggests that trust in the technology’s capabilities, although important, may not be sufficient to drive adoption, as users may hold cautious or nuanced views. Satisfaction, by contrast, reflects a more immediate and emotionally resonant response, grounded in actual user experience. When users feel that ChatGPT supports their work and delivers tangible value, this sense of fulfillment becomes a strong motivator for adoption.

These insights carry significant implications for firms seeking to integrate ChatGPT into SC workflows. The strong influence of satisfaction suggests that widespread acceptance depends less on trust alone and more on users’ positive interactions with the tool [76]. Therefore, organizations should invest in onboarding, training, and user-centered design to ensure that employees find ChatGPT intuitive, reliable, and relevant to their tasks. At the same time, the finding that trust does not significantly predict adoption intention highlights the need to demystify ChatGPT’s functionality, helping users understand not only what the tool can do but also how and why it supports their SC decision-making.

The role of technology anxiety as a moderator in the adoption process highlights the need to address psychological barriers to AI adoption [77]. In industries where Gen-AI is perceived as a disruptive force, such as manufacturing and transportation, companies must invest in change management strategies to alleviate workers' concerns about job displacement and the complexity of new technologies [78]. For example, Tesla has successfully integrated AI into its manufacturing processes by emphasizing human-AI collaboration rather than replacement, which has helped reduce anxiety among workers and fostered greater acceptance of the technology.

A. Theoretical implication

This study makes several key theoretical contributions to the literature on supply chain management, technology adoption, and the integration of generative AI. First, it extends the TTF theory by applying it to a novel AI context—ChatGPT—in the context of supply chain operations. While TTF has traditionally been used to assess the alignment between users, tasks, and structured information systems, this study demonstrates its relevance in evaluating conversational AI tools that support both analytical and decision-making functions. By identifying specific supply chain tasks—optimization, coordination, and sustainability—where ChatGPT enhances task performance, the study provides empirical support for TTF in dynamic, knowledge-intensive environments. The results confirm that when generative AI is perceived as well-aligned with operational needs, it has a positive impact on user evaluations and subsequent technology-related behaviors.

Second, the study advances the SOR framework by incorporating TTF as the external stimulus and examining its influence on users' cognitive (trust) and emotional (satisfaction) responses, which together form the organism stage. This integration helps bridge the gap between functional fit (from the TTF perspective) and psychological readiness (from the SOR perspective). By demonstrating that TTF serves as a key trigger for internal evaluations that lead to adoption, the study enhances the explanatory power of the SOR framework in technology adoption contexts, particularly in enterprise settings where trust and satisfaction are crucial precursors to behavioral change.

Furthermore, the study highlights the moderating role of technology anxiety, offering a nuanced understanding of how negative emotional states can weaken the positive effects of trust and satisfaction on the intention to adopt ChatGPT. While much of the existing literature treats trust and satisfaction as sufficient for adoption, this study reveals that psychological barriers such as anxiety can undermine these relationships. This insight contributes to both the TTF and SOR literature by emphasizing the importance of emotional inhibitors in shaping technology acceptance, particularly in high-stakes, operationally critical domains like supply chain management.

Finally, the study contributes to the emerging body of research on Gen-AI in organizational contexts, where empirical evidence remains scarce. By focusing on ChatGPT's integration in SCM, this research provides an initial empirical foundation for understanding how Gen-AI tools are perceived, evaluated, and adopted by professionals in data-driven and operationally complex environments. This theoretical foundation lays the groundwork for future research examining the interplay between AI capabilities, human cognition, and organizational adoption behavior across diverse industries.

B. Managerial implication

The findings of this study provide valuable insights for supply chain managers, digital transformation leaders, and organizations seeking to integrate ChatGPT or similar Gen-AI tools into their supply chain operations. First, the strong relationship between ChatGPT's role in supply chain optimization, coordination, and sustainability and its perceived TTF indicates that organizations should carefully assess and align AI capabilities with specific SC tasks. For instance, ChatGPT can enhance SC optimization through intelligent analysis of logistics and inventory data, support coordination by streamlining communication among internal departments and external partners, and contribute to sustainability by generating reports and recommendations that reduce waste and inefficiencies in resource utilization. By clearly mapping ChatGPT's strengths to targeted SC tasks, managers can improve its perceived utility and ensure that the technology is seen as a value-adding asset rather than an experimental tool.

Moreover, the results indicate that a strong TTF is associated with higher levels of trust and satisfaction, which in turn positively influence the intention to adopt ChatGPT. This highlights the importance of delivering a user experience that builds confidence and meets user expectations. Managers should focus on transparent integration processes, providing employees with examples of ChatGPT's successful task performance, and maintaining continuous technical support. Fostering satisfaction involves ensuring that the technology is not only functional but also easy to use and responsive to user needs. In parallel, building trust requires consistency in outputs, system transparency, and clear communication about how ChatGPT generates responses or recommendations. However, the study also reveals that technology anxiety weakens the relationship between trust, satisfaction, and the intention to adopt ChatGPT. This suggests that even when users perceive the technology as useful and trustworthy, high levels of anxiety about interacting with AI can still undermine adoption. To mitigate this, organizations must invest in user training and awareness programs that demystify how ChatGPT works and reduce fears associated with automation, job displacement, or the complexity of the system. Creating a psychologically safe environment where employees feel encouraged to experiment with ChatGPT without fear of failure or judgment is essential to overcoming anxiety-driven resistance. Ultimately, organizations should adopt a proactive and iterative approach to integrating ChatGPT, collecting ongoing feedback from users, monitoring system performance, and allowing the AI's role to evolve in tandem with operational needs. In doing so, managers can reinforce the alignment between technology and task demands while cultivating a workforce that is confident, engaged, and open to AI-driven innovation.

C. Policy implications

The findings of this study have important implications for policymakers, particularly those involved in shaping digital transformation, workforce development, and responsible AI governance in supply chain contexts. As Gen-AI tools such as ChatGPT gain traction in enterprise environments, policy interventions are needed to ensure their adoption contributes not only to operational efficiency but also to ethical, inclusive, and sustainable technological progress.

First, the results highlight the crucial role of task-technology alignment in influencing adoption outcomes. Policymakers should support frameworks and standards that guide organizations in evaluating and implementing AI technologies based on task fit rather than broad digitalization agendas. Public institutions and industry bodies can develop sector-specific AI task fit assessment guidelines to help firms identify where tools like ChatGPT offer the most value. These guidelines can reduce resource misallocation and improve the success rate of AI adoption in supply chains. Second, the study highlights the psychological aspects of AI acceptance, demonstrating how trust, satisfaction, and technology anxiety impact employee engagement with generative AI. Policymakers should prioritize the human-centered dimensions of AI adoption by encouraging or mandating employee training programs, awareness campaigns, and digital literacy initiatives. Public-private partnerships can help build competency among the workforce by offering certification programs and upskilling pathways tailored to conversational AI tools in logistics, procurement, and operations.

Third, the moderating role of technology anxiety indicates that regulatory oversight should address not only data and algorithmic fairness but also emotional and psychological safety in the workplace. As organizations integrate Gen-AI tools into their core functions, policies should promote ethical AI practices that include transparency, user control, explainability, and consideration of mental well-being. Regulatory bodies can encourage the inclusion of employee feedback mechanisms and AI ethics audits as part of AI deployment strategies in supply chains.

Ultimately, the increasing influence of ChatGPT-like tools in shaping decision-making necessitates policy frameworks that strike a balance between automation and accountability. Governments and industry regulators should provide clear guidance on responsibility and liability when AI-generated insights are used in strategic supply chain decisions. This includes policies around data privacy, misinformation mitigation, and risk governance for AI-enabled operations.

VI. CONCLUSION, LIMITATION, AND FUTURE RESEARCH

This study offers a comprehensive and empirically grounded analysis of the factors influencing the adoption of ChatGPT in SCM, integrating the TTF theory and the SOR framework. The findings highlight that ChatGPT enhances supply chain functions—particularly optimization, sustainability, and coordination—when its capabilities are perceived to align with task requirements, thereby strengthening its task-technology fit. This perceived fit, in turn, fosters user trust and satisfaction, which are critical drivers of adoption intentions. Importantly, the study reveals that technology anxiety significantly moderates the relationship between these psychological enablers and the intention to adopt ChatGPT, underscoring the need to address emotional and cognitive barriers in AI integration efforts.

The study contributes to the theoretical advancement of both TTF and SOR by demonstrating their combined explanatory power in the context of Gen-AI adoption in enterprise settings. It also offers actionable managerial and policy insights for supporting the human-centered integration of conversational AI tools within supply chains. From a practical perspective, organizations seeking to deploy Gen-AI technologies must go beyond technical implementation and prioritize user experience, trust-building, and anxiety mitigation to enable successful adoption.

Despite its contributions, the study is subject to several limitations. First, the cross-sectional design restricts the ability to observe changes in perception and behavior over time. Future research should employ longitudinal designs to capture the evolution of trust, satisfaction, and technology anxiety as users gain more experience with ChatGPT. Second, while this study draws on a diverse industry sample, future studies could explore sector-specific adoption patterns and extend the model to other functional areas such as procurement, sourcing, and reverse logistics. Finally, incorporating additional constructs such as perceived risk, AI literacy, or organizational support may further enrich the understanding of adoption dynamics.

Future research could explore how user experience levels shape perceptions and adoption behavior as a control variable, which may offer deeper insights into how trust, satisfaction, and anxiety influence adoption across different usage stages. While this study applies the TTF and SOR frameworks in line with prior research, future studies could extend these models by accounting for the interactive, adaptive, and co-learning nature of Gen-AI tools. In particular, future work should investigate how ChatGPT's human-like qualities—such as anthropomorphism, perceived agency, or conversational responsiveness—may reshape traditional constructs, including trust, satisfaction, and anxiety, within AI adoption frameworks.

Appendix A

Measured with a 5-point Likert scale (1= Strongly disagree, 2= Disagree, 3= Natural, 4= Agree, 5= Strongly agree)

Variables	Items	Reference
SC Optimization	ChatGPT can help supply chains enhance process efficiency and cost reduction.	[3]
	ChatGPT can support predictive maintenance on equipment.	
	ChatGPT can improve data analysis to support all supply chain processes	
	ChatGPT can simplify the complex processes involved in logistics by reducing waste and inefficiencies such as wait times	
	ChatGPT can support a warehouse management (e.g., visibility of real-time inventory and optimization of storage space)	
	ChatGPT can aid in route optimization by evaluating shipping data and providing recommendations to speed up deliveries	
	ChatGPT can automate routine tasks such as tracking and monitoring shipments and ordering processes.	
SC Adaptability	ChatGPT can help provide a quick and easy response to supply chain challenges.	[3], [61]
	Supply chain interruptions can be managed using ChatGPT.	
	ChatGPT can help with demand forecasting and planning by analyzing historical data, market trends, and customer feedback to assist in demand forecasting.	
	ChatGPT can help our firm maintain continuous high situational awareness.	
SC Sustainability	ChatGPT can provide sustainability reports, assist in evaluating suppliers, and help map supply chain sources with less risk.	[3], [62]
	ChatGPT can help reduce waste in supply chains and support supply chain decision-makers.	
	ChatGPT can help firms to achieve resource efficiency across supply chain processes.	
	ChatGPT can help firms to upgrade their compliance with environmental standards.	
SC Coordination	ChatGPT can streamline supplier communication (e.g. solving supply issues through more effective communication).	[3]
	ChatGPT can support promotional activities	

	of marketing and workforce management by acting as an effective training and guidance tool. ChatGPT can enhance coordination among our firm's internal departments. ChatGPT can streamline customer communication.	
Task Technology Fit	In my opinion, ChatGPT functions are well-suited for supply chain tasks. In my opinion, ChatGPT's functions are sufficient for supply chain tasks. In my opinion, ChatGPT functions meet the requirements for supply chain tasks.	[14], [63]
Intention to Adopt ChatGPT in Supply Chain	In the near future, our firm will use ChatGPT for supply chain operations. I predict that our firm will regularly use ChatGPT in the future. I think our firm's employees are comfortable using ChatGPT.	[66]
Satisfaction in ChatGPT	I am generally pleased with ChatGPT usage. I am very satisfied with ChatGPT. I am happy with ChatGPT. Overall, I was satisfied with ChatGPT.	[48]
Trust in ChatGPT	ChatGPT is honest and truthful. ChatGPT is capable of addressing the issues. ChatGPT's response and advice can meet my expectations. I trust the suggestions and decisions provided by ChatGPT.	[64]
Technology Anxiety	ChatGPT is somewhat intimidating for me. I have avoided using ChatGPT frequently because it is unfamiliar for me to speak to a machine. I have difficulty understanding most technological matters related to ChatGPT.	[65]

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