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Human-AI Collaboration and Distribution Planning Effectiveness: Evidence from Retail Operations

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Abstract

Purpose: The increasing adoption of artificial intelligence (AI)-based decision support systems has transformed distribution planning processes in retail operations; however, empirical evidence explaining how human-AI collaboration influences distribution planning effectiveness remains limited. Drawing on Socio-Technical Systems theory, Human-AI Interaction theory, and Trust in Automation theory, this study examines how AI decision transparency, AI interpretability, and human-AI decision alignment relates to distribution planning effectiveness, considering the mediating role of planner trust in AI systems and the moderating role of task complexity. **Methodology:** Survey data were collected from 320 distribution planners and supply chain professionals working in retail firms in South Korea. The proposed mediation-moderation model was tested using partial least squares structural equation modeling (PLS-SEM). **Results:** The findings show that AI decision transparency and AI interpretability are positively associated with planner trust in AI systems, which in turn is linked to higher distribution planning effectiveness. Human-AI decision alignment exhibits a strong direct association with planning effectiveness. Task complexity significantly strengthens the relationship between planner trust and planning effectiveness. **Conclusions:** The study demonstrates that distribution planning effectiveness in retail operations depends not only on AI system capabilities but also on socio-technical alignment between AI systems and human planners. Transparent, interpretable, and trusted AI systems provide greater value in complex distribution planning environments.

Keywords : Human-AI Collaboration; Distribution Planning; Planner Trust; AI Transparency; Task Complexity; Retail Operations.

JEL Classification Code : L14; L81; M11; O33

1. Introduction

Retail distribution planning has become increasingly complex due to demand volatility, shortened product life cycles, omnichannel fulfillment structures, and heightened customer service expectations. To cope with these challenges, retail firms are increasingly adopting artificial intelligence (AI)-based decision support systems to assist with demand forecasting, inventory replenishment, and

distribution coordination (Choi et al., 2018; Ivanov & Dolgui, 2020). AI-driven analytics enable organizations to process large volumes of data in real time and generate planning recommendations that exceed traditional analytical capabilities (Wamba et al., 2021).

Despite the growing diffusion of AI in distribution and logistics, empirical evidence regarding its effectiveness remains mixed. Prior research has primarily emphasized technology adoption, digital capabilities and algorithmic

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accuracy, often assuming that superior technology directly translates into better operational outcomes (Kache & Seuring, 2017; Queiroz et al., 2020). However, distribution planning decisions are rarely made by AI systems alone. Instead, they emerge from continuous interaction between human planners and AI-generated recommendations, where human judgment, contextual knowledge, and experiential insight remain essential (Rai et al., 2019).

Recent studies in information systems and organizational research highlight that the value of AI lies not only in technical sophistication but also in the quality of human–AI collaboration. Characteristics such as decision transparency, interpretability, and alignment between algorithmic outputs and human judgment significantly shape how decision-makers understand, evaluate and utilize AI systems (Faraj et al., 2018; Shrestha et al., 2019). However, these human-centered perspectives remain underexplored in distribution science research, which continues to prioritize structural and technological enablers over behavioral mechanisms.

One particularly critical yet insufficiently examined mechanism is trust in AI systems. Trust determines whether planners rely on, override, or ignore AI-generated recommendations, especially under conditions of uncertainty and operational risk (Lee & See, 2004; Glikson & Woolley, 2020). Even highly accurate AI systems may fail to improve planning outcomes if users lack confidence in their recommendations. Conversely, excessive or uncalibrated trust may lead to overreliance and decision errors (Parasuraman & Riley, 1997). These dynamics suggest that trust plays a central mediating role between AI system characteristics and distribution planning effectiveness.

In addition, distribution planning tasks differ substantially in their level of task complexity. Retail planners frequently operate in environments characterized by uncertain demand, interdependent distribution nodes, frequent exceptions, and time pressure. Decision-making research indicates that as task complexity increases, reliance on decision support systems becomes more critical and trust becomes a more salient determinant of decision quality (Bonaccio et al., 2010; Rai et al., 2020). Nevertheless, the moderating role of task complexity in AI-enabled distribution planning has received limited empirical attention.

To address these gaps, this study examines how human–AI collaboration influences distribution planning effectiveness in retail operations, with a particular focus on the mediating role of planner trust in AI systems and the moderating role of task complexity. The study is grounded in Socio-Technical Systems (STS) theory, which posits that organizational performance outcomes emerge from the joint optimization of technical and social subsystems rather than from technology or human actors in isolation (Trist &

Bamforth, 1951; Baxter & Sommerville, 2011). In this context, AI-based planning systems represent the technical subsystem, while planners' trust, judgment, and interaction with AI outputs constitute the social subsystem. The STS perspective is complemented by Human–AI Interaction theory, which emphasizes transparency, interpretability, and alignment as key conditions for effective collaboration between humans and intelligent systems (Faraj et al., 2018; Shrestha et al., 2019), and by Trust in Automation theory, which explains how trust shapes appropriate reliance on automated systems under uncertainty (Lee & See, 2004; Glikson & Woolley, 2020). Together, these perspectives provide a robust theoretical foundation for understanding AI-enabled distribution planning as a human-centered, context-dependent process.

Using survey data collected from retail distribution and planning professionals in South Korea, this study employs partial least squares structural equation modeling (PLS-SEM) to test the proposed mediation–moderation model. South Korea offers a suitable empirical setting due to its advanced adoption of AI-driven planning systems and highly complex retail distribution environment (Ivanov & Dolgui, 2020; Choi et al., 2018).

This study makes three key contributions to the distribution science literature. First, it advances distribution planning research by conceptualizing human–AI collaboration as a socio-technical capability rather than a purely technological input. Second, it identifies planner trust in AI systems as a central behavioral mechanism through which AI system characteristics influence planning effectiveness. Third, it demonstrates how task complexity conditions the value of trust in AI-supported planning, offering a more nuanced understanding of when human–AI collaboration is most effective.

2. Literature Review and Hypotheses Development

2.1. Theoretical Framework

This study is grounded primarily in Socio-Technical Systems (STS) theory, which posits that organizational performance outcomes emerge from the joint optimization of technical systems and social systems, rather than from technology or human actors in isolation (Trist & Bamforth, 1951; Baxter & Sommerville, 2011; Rehman & Ha, 2021). STS theory emphasizes that technologies must be effectively integrated with human skills, behaviors, and organizational routines to generate performance benefits. Misalignment between technical capabilities and social practices can reduce system effectiveness and lead to suboptimal outcomes.

In the context of retail distribution planning, AI-based decision support systems constitute the technical subsystem, while distribution planners' judgment, trust, and interaction with AI recommendations represent the social subsystem. STS theory suggests that distribution planning effectiveness depends on how well these subsystems are aligned and jointly optimized (Jarrahi, 2018).

To explain how planners interact with AI systems at the micro level, this study further draws on Human–AI Interaction theory, which highlights transparency, interpretability, and alignment as key factors shaping users' understanding, evaluation, and utilization of intelligent systems (Faraj et al., 2018; Shrestha et al., 2019). Human–AI Interaction research views AI as an augmentative technology that supports, rather than replaces, human decision-making (Rai et al., 2019).

In addition, the study incorporates Trust in Automation theory, which explains how users develop appropriate reliance on automated systems under conditions of uncertainty and risk (Lee & See, 2004; Parasuraman & Riley, 1997). This theory identifies trust as a central behavioral mechanism linking system characteristics to decision quality and performance outcomes (Glikson & Woolley, 2020). Together, these perspectives provide a robust theoretical foundation for examining AI-enabled distribution planning as a human-centered and context-dependent process.

2.2. AI-Based Decision Support Systems in Distribution Planning

AI-based decision support systems are increasingly deployed in retail distribution planning to improve demand forecasting, inventory replenishment, and coordination across distribution networks. Prior research indicates that AI-driven analytics enhance planning quality by processing large volumes of data, identifying complex patterns, and generating real-time recommendations (Choi et al., 2018; Ivanov & Dolgui, 2020). These systems are particularly valuable in retail environments characterized by demand volatility, short product life cycles, and omnichannel fulfillment requirements.

However, existing research in distribution and logistics has largely emphasized technology adoption and digital capabilities, often assuming that advanced algorithms directly lead to improved operational performance (Kache & Seuring, 2017; Queiroz et al., 2020). Such technology-centric approaches overlook the fact that distribution planning decisions remain human-in-the-loop processes, where planners must interpret, evaluate, and sometimes override AI-generated recommendations (Rai et al., 2019). Consistent with STS theory, the effectiveness of AI-supported planning therefore depends on how planners

interact with and utilize AI outputs rather than on algorithmic accuracy alone.

2.3. AI Decision Transparency and Planner Trust

AI decision transparency refers to the extent to which AI systems clearly communicate how and why specific recommendations are generated. Human–AI Interaction theory suggests that transparency reduces uncertainty by enabling users to understand system logic and decision rationale (Shrestha et al., 2019). Trust in Automation theory further argues that transparent systems promote appropriate reliance by allowing users to assess system competence and limitations (Lee & See, 2004).

In retail distribution planning, opaque AI recommendations may be perceived as risky or unreliable, leading planners to discount or override system outputs. Conversely, transparent AI systems foster confidence and trust, encouraging planners to integrate AI-generated insights into their decision-making processes (Shin, 2021). From an STS perspective, transparency enhances socio-technical alignment by facilitating meaningful interaction between planners and AI systems.

H1: *AI decision transparency positively influences planner trust in AI systems.*

2.4. AI Interpretability and Planner Trust

AI interpretability reflects planners' perceived ability to understand, evaluate, and assess the plausibility of AI-generated outputs. While transparency focuses on the visibility of decision logic, interpretability emphasizes users' cognitive ability to make sense of AI recommendations. Research on Human–AI Interaction indicates that interpretable systems reduce cognitive burden and support informed judgment, particularly in complex decision environments (Rai et al., 2020).

In retail distribution planning, planners must reconcile AI-generated forecasts with contextual factors such as promotions, seasonality, and supply disruptions. When AI outputs are interpretable, planners are more likely to perceive them as reliable and useful, thereby strengthening trust in AI systems (Glikson & Woolley, 2020). Consistent with STS theory, interpretability supports effective integration of technical outputs into social decision-making processes.

H2: *AI interpretability positively influences planner trust in AI systems.*

2.5. Human–AI Decision Alignment and Distribution Planning Effectiveness

Human–AI decision alignment refers to the degree to

which AI-generated recommendations are consistent with planners' professional judgment and experiential knowledge. STS theory emphasizes that performance improves when technical outputs complement human expertise rather than conflict with it (Baxter & Sommerville, 2011). Similarly, Human–AI Interaction research highlights alignment as a critical condition for effective collaboration between humans and intelligent systems (Faraj et al., 2018; Rehman, 2025).

In distribution planning, alignment reduces decision conflict, accelerates planning cycles, and enhances coordination across distribution nodes. When planners perceive AI recommendations as aligned with their contextual understanding, they are more likely to implement decisions efficiently, leading to improved planning outcomes such as forecast accuracy and replenishment quality (Choi et al., 2018).

H3: *Human–AI decision alignment positively influences distribution planning effectiveness.*

2.6. Planner Trust in AI Systems and Distribution Planning Effectiveness

Planner trust in AI systems reflects planners' willingness to rely on AI-generated recommendations under conditions of uncertainty and operational risk. Trust in Automation theory posits that trust is a central determinant of system use and effectiveness, particularly in high-stakes decision environments (Lee & See, 2004). In distribution planning, insufficient trust may result in underutilization of AI systems, while appropriate trust enables planners to leverage AI insights without abandoning critical judgment.

From an STS perspective, trust functions as a linking mechanism between technical system characteristics and social system behavior. When trust is established, AI systems are more effectively embedded in planning routines, leading to superior planning outcomes (Glikson & Woolley, 2020).

H4: *Planner trust in AI systems positively influences distribution planning effectiveness.*

2.7. Mediating Role of Planner Trust in AI Systems

Although AI decision transparency and interpretability enhance planners' understanding of AI systems, their effects on planning effectiveness are unlikely to be purely direct. Trust in Automation theory suggests that system characteristics influence performance outcomes primarily through their impact on users' trust and reliance behaviors (Parasuraman & Riley, 1997; Rehman, 2025). Accordingly, planner trust is expected to mediate the relationships between AI system characteristics and distribution planning effectiveness.

Consistent with STS theory, trust represents the behavioral mechanism through which socio-technical alignment translates into operational outcomes. Without trust, even transparent and interpretable AI systems may fail to improve distribution planning effectiveness.

H5: *Planner trust in AI systems mediates the relationships between (a) AI decision transparency and distribution planning effectiveness and (b) AI interpretability and distribution planning effectiveness.*

2.8. Moderating Role of Task Complexity

Task complexity refers to the degree of uncertainty, interdependence, and information-processing demands associated with distribution planning tasks. Decision-making research indicates that as task complexity increases, reliance on decision support systems becomes more critical and trust becomes a more salient determinant of decision quality (Bonaccio et al., 2010; Rai et al., 2020). Trust in Automation theory further argues that trust plays a more prominent role in complex tasks, where cognitive demands and uncertainty are high (Lee & See, 2004).

In highly complex retail distribution environments, trusted AI systems can reduce cognitive overload and support more effective decision-making. Accordingly, task complexity is expected to strengthen the relationship between planner trust and distribution planning effectiveness, consistent with STS theory's emphasis on contextual conditions.

H6: *Task complexity positively moderates the relationship between planner trust in AI systems and distribution planning effectiveness, such that the relationship is stronger under higher task complexity.*

2.9. Summary of the Research Model

In summary, this study integrates Socio-Technical Systems theory, Human–AI Interaction theory, and Trust in Automation theory to explain how AI system characteristics influence distribution planning effectiveness through human-centered mechanisms. The proposed model positions planner trust as a key mediating variable and task complexity as a critical boundary condition, offering a theoretically grounded framework for understanding human–AI collaboration in retail distribution planning.

3. Methodology

3.1. Research Design

This study adopts a quantitative, cross-sectional survey research design to empirically examine the effects of

human–AI collaboration on distribution planning effectiveness in retail operations. A survey-based approach is appropriate for capturing planners' perceptions, experiences, and behavioral responses to AI-based decision support systems used in routine distribution planning activities (Rai et al., 2019).

Given the predictive and theory-building nature of the proposed model, which includes mediating and moderating relationships, the data were analyzed using partial least squares structural equation modeling (PLS-SEM). PLS-SEM is particularly suitable for complex models, non-normal data, and exploratory theory development in operations and information systems research (Hair et al., 2022; Sarstedt et al., 2017). Given the cross-sectional survey design, the relationships examined in this study should be interpreted as associational rather than causal.

3.2. Research Context

The empirical context of this study is the retail industry in South Korea. South Korea represents an appropriate research setting due to its advanced adoption of AI-driven analytics and decision support systems in retail distribution planning, including demand forecasting, inventory replenishment, and logistics coordination (Choi et al., 2018; Ivanov & Dolgui, 2020).

Retail distribution in South Korea is characterized by dense urban logistics networks, high delivery speed expectations, and omnichannel fulfillment structures. These characteristics increase decision uncertainty and task complexity, making human–AI collaboration particularly relevant and theoretically appropriate for investigation under the Socio-Technical Systems framework (Baxter & Sommerville, 2011). Accordingly, South Korea can be viewed as a theoretically appropriate and technologically advanced ('lead') context for examining human–AI collaboration under conditions of high AI maturity.

3.3. Respondents and Sampling

The target respondents for this study were distribution planners, demand planners, inventory and replenishment managers, and supply chain or operations managers employed in South Korean retail firms that utilize AI-based or advanced analytics decision support systems for distribution planning.

These respondents were selected because they are the primary users of AI-generated planning recommendations and retain responsibility for final decision-making. Their direct involvement in planning activities enables them to meaningfully evaluate AI decision transparency, interpretability, human–AI decision alignment, trust in AI systems, and distribution planning effectiveness (Faraj et al.,

2018; Rai et al., 2019).

A purposive sampling strategy was employed to ensure that only respondents with relevant experience in AI-supported planning participated in the study. A minimum sample size of 300 valid responses was targeted, exceeding recommended thresholds for PLS-SEM analysis and ensuring adequate statistical power (Hair et al., 2022).

3.4. Measurement of Constructs

Consistent with behavioral operations and information systems research, distribution planning effectiveness was measured using perceptual self-reported items. Following key informant theory, respondents were selected based on their direct involvement and responsibility for distribution planning decisions, making them appropriate and knowledgeable informants for assessing planning effectiveness. All constructs were measured using multi-item scales adapted from established literature in information systems, operations management, and human–AI interaction research. Items were contextualized to the retail distribution planning setting and measured on a five-point Likert scale ranging from 1 (*strongly disagree*) to 5 (*strongly agree*).

- AI Decision Transparency was measured by items capturing the extent to which AI systems clearly explain how and why planning recommendations are generated, adapted from research on explainable AI and algorithmic transparency (Shin, 2021).
- AI Interpretability reflects planners' perceived ability to understand and evaluate AI-generated outputs and was adapted from human–AI decision-making literature (Rai et al., 2020).
- Human–AI Decision Alignment measures the consistency between AI recommendations and planners' professional judgment, adapted from studies on human–AI collaboration (Shrestha et al., 2019).
- Planner Trust in AI Systems assesses confidence in the reliability, accuracy, and usefulness of AI-supported planning decisions, drawing on established trust-in-automation scales (Lee & See, 2004; Glikson & Woolley, 2020).
- Distribution Planning Effectiveness captures planning outcomes such as forecast accuracy, coordination efficiency, and decision quality, adapted from distribution and operations management research (Choi et al., 2018).

- Task Complexity measures perceived uncertainty, interdependence, and information-processing demands associated with distribution planning tasks (Bonaccio et al., 2010).
- Planner Experience was included as a control variable and measured as the number of years of professional experience in distribution or supply chain roles.

3.5. Data Collection Procedure

Data were collected using a self-administered online questionnaire distributed through professional networks, industry contacts, and supply chain associations in South Korea. Prior to full-scale data collection, the questionnaire was pilot-tested with a small group of retail distribution professionals to ensure item clarity, relevance, and content validity.

To mitigate common method bias, several procedural remedies were applied. Respondents were assured of anonymity and confidentiality, and the questionnaire design included careful item wording and psychological separation of predictor and criterion variables (Podsakoff et al., 2003).

3.6. Data Analysis

Data analysis was conducted using PLS-SEM with SmartPLS software. Following established guidelines, the analysis proceeded in two stages. First, the measurement model was evaluated by examining indicator reliability, internal consistency reliability (Cronbach's alpha and composite reliability), convergent validity (average variance extracted) and discriminant validity using the heterotrait-monotrait (HTMT) ratio (Henseler et al., 2015; Hair et al., 2022). Discriminant validity was assessed using the heterotrait-monotrait (HTMT) ratio, which has been shown to be a more reliable criterion than the Fornell-Larcker approach in variance-based SEM.

Second, the structural model was assessed by examining path coefficients, coefficients of determination (R^2), effect sizes (f^2), and predictive relevance (Q^2). The mediating effect of planner trust in AI systems was tested using a bootstrapping procedure with 5,000 resamples, while the moderating effect of task complexity was examined using an interaction term approach, consistent with PLS-SEM best practices (Hair et al., 2022; Rehman, 2026).

3.7. Common Method Bias Assessment

In addition to procedural remedies, a post-hoc statistical assessment was conducted to evaluate the potential impact of common method bias (CMB). Following Kock (2015), a

full collinearity variance inflation factor (VIF) approach was employed by regressing all latent constructs on a common factor. The resulting VIF values ranged below the conservative threshold of 3.3, indicating that common method bias is unlikely to pose a serious concern in this study.

4. Results and Discussion

4.1. Conceptual Research Model

Figure 1 presents the conceptual research model developed based on Socio-Technical Systems theory, Human-AI Interaction theory, and Trust in Automation theory. The model proposes that AI decision transparency and AI interpretability influence planner trust in AI systems, which subsequently affects distribution planning effectiveness. In addition, human-AI decision alignment is hypothesized to directly improve distribution planning effectiveness, while task complexity moderates the relationship between planner trust and distribution planning effectiveness. This model reflects the joint optimization of technical and social subsystems and provides the theoretical foundation for the empirical analysis.

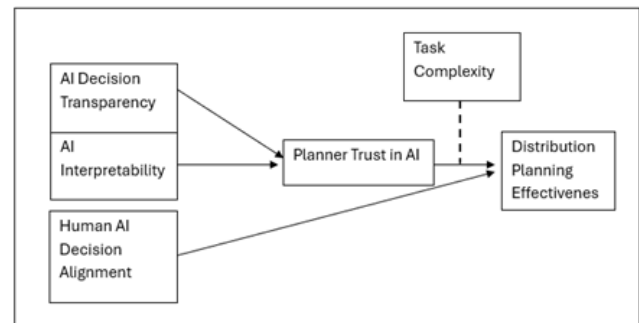


Figure 1: Conceptual Research Model

4.2. Respondent Demographic Profile

Table 1 presents the demographic characteristics of the respondents. The sample is dominated by distribution planners and supply chain or operations managers, indicating that respondents are directly involved in AI-supported distribution planning. A substantial proportion of respondents possess more than five years of professional experience, suggesting that they have sufficient exposure to both traditional and AI-driven planning systems. This demographic profile confirms the appropriateness and credibility of the sample for examining human-AI collaboration in retail distribution planning.

Table 1: Demographic Profile of Respondents (N = 320)

Variable	Category	Frequency	Percentage (%)
Gender	Male	214	66.9
	Female	106	33.1
Age	Below 30	54	16.9
	30–39	132	41.3
	40–49	96	30.0
	50+	38	11.8
Education	Bachelor’s	142	44.4
	Master’s	138	43.1
	Doctorate	40	12.5
Job Role	Planner	98	30.6
	Inventory Manager	84	26.3
	SC/Operations Manager	138	43.1
Experience	<5 years	68	21.3
	5–10 years	144	45.0
	>10 years	108	33.7

Table 2 reports the results of the reliability and convergent validity assessment. All indicator loadings exceed the recommended threshold of 0.70, indicating satisfactory indicator reliability. Cronbach’s alpha and composite reliability values are above 0.70 for all constructs, confirming strong internal consistency. In addition, all AVE values exceed 0.50, demonstrating adequate convergent validity. These results indicate that the measurement scales are reliable and suitable for structural model analysis.

Table 2: Measurement Model Assessment

Construct	Indicator Loadings	Cronbach’s α	CR	AVE
AI Decision Transparency	0.78–0.86	0.88	0.91	0.68
AI Interpretability	0.76–0.85	0.87	0.90	0.66
Human–AI Decision Alignment	0.79–0.88	0.89	0.92	0.70
Planner Trust in AI Systems	0.80–0.89	0.90	0.93	0.72
Distribution Planning Effectiveness	0.77–0.86	0.88	0.91	0.67
Task Complexity	0.75–0.84	0.86	0.90	0.64

4.3. Measurement Model Assessment

Table 3 presents discriminant validity results using the HTMT criterion. All HTMT values are below the conservative threshold of 0.85, indicating that the constructs are empirically distinct. This confirms that AI transparency, AI interpretability, human–AI decision alignment, planner trust, task complexity, and distribution planning effectiveness capture different theoretical concepts and do not suffer from multicollinearity or conceptual overlap.

Table 3: Discriminant Validity (HTMT Ratios)

Constructs	ADT	AI-I	HADA	Trust	DPE	TC
ADT	—					
AI-I	0.62	—				
HADA	0.58	0.60	—			
Trust	0.67	0.65	0.59	—		
DPE	0.55	0.53	0.69	0.71	—	
TC	0.41	0.39	0.44	0.46	0.48	—

4.4. Structural Model Results

Table 4 reports the results of hypothesis testing. AI decision transparency and AI interpretability both have significant positive effects on planner trust in AI systems, supporting H1 and H2. Human–AI decision alignment exhibits a strong positive effect on distribution planning effectiveness, supporting H3. Additionally, planner trust in AI systems significantly improves distribution planning effectiveness, supporting H4. These results confirm that both technical system characteristics and behavioral mechanisms play critical roles in AI-enabled planning.

Table 4: Hypothesis Testing Results

Hypothesis	Path	β	t-value	p-value	Decision
H1	Transparency → Trust	0.32	6.14	<0.001	Supported
H2	Interpretability → Trust	0.29	5.67	<0.001	Supported
H3	Alignment → Effectiveness	0.34	6.48	<0.001	Supported
H4	Trust → Effectiveness	0.31	5.89	<0.001	Supported

Table 5 presents the explanatory power of the structural model. The model explains 41% of the variance in planner trust and 47% of the variance in distribution planning effectiveness, indicating moderate-to-strong explanatory power. The f² values show that human–AI decision alignment and planner trust have meaningful effect sizes, highlighting their substantive importance in explaining planning effectiveness.

Table 5: Model Explanatory Power

Endogenous Construct	R ²	Key f ² Values
Planner Trust	0.41	Transparency (0.18), Interpretability (0.15)
Planning Effectiveness	0.47	Alignment (0.21), Trust (0.19)

4.5. Mediation Analysis

Table 6 reports the results of the mediation analysis. Planner trust in AI systems significantly mediates the relationship between AI decision transparency, AI

interpretability, and distribution planning effectiveness. This indicates that transparency and interpretability enhance planning effectiveness primarily by increasing planners' trust in AI systems rather than through direct effects alone, supporting H5.

Table 6: Mediating Effects of Planner Trust

Indirect Relationship	β	t-value	p-value	Result
Transparency → Trust → Effectiveness	0.10	4.92	<0.001	Supported
Interpretability → Trust → Effectiveness	0.09	4.41	<0.001	Supported

4.6. Moderation Analysis

Table 7 presents the moderation analysis results. The positive and significant interaction effect indicates that task complexity strengthens the relationship between planner trust and distribution planning effectiveness. This suggests that trust in AI systems becomes more influential when distribution planning tasks are highly complex, supporting H6 and highlighting the importance of contextual conditions in AI-supported decision-making.

Table 7: Moderating Effect of Task Complexity

Interaction Effect	β	t-value	p-value	Result
Trust × Task Complexity → Effectiveness	0.14	3.26	0.001	Supported

5. Conclusions and Future Research Directions

5.1. Conclusions

This study examined the role of human–AI collaboration in enhancing distribution planning effectiveness in retail operations by integrating Socio-Technical Systems (STS) theory, Human–AI Interaction theory, and Trust in Automation theory. Using survey data from retail distribution professionals in South Korea and analyzing the data through PLS-SEM, the study provides several important conclusions. First, the findings demonstrate that AI decision transparency and AI interpretability are critical antecedents of planner trust in AI systems. When AI-based decision support systems clearly explain how recommendations are generated and produce outputs that planners can cognitively evaluate, planners are more likely to trust and rely on these systems. This finding aligns with prior research emphasizing explainability and interpretability as foundations for effective human–AI interaction (Shin, 2021; Faraj et al., 2018; Shrestha et al., 2019; Rehman, 2026). Second, the results confirm that planner trust in AI systems plays a central mediating role in

translating AI system characteristics into improved distribution planning effectiveness. Transparent and interpretable AI systems enhance planning outcomes primarily by fostering trust rather than through direct performance effects. This conclusion reinforces Trust in Automation theory, which highlights trust as a key mechanism shaping appropriate reliance on automated systems (Lee & See, 2004; Parasuraman & Riley, 1997) and is consistent with recent empirical evidence on trust in artificial intelligence (Glikson & Woolley, 2020). Third, human–AI decision alignment was found to have a strong and direct effect on distribution planning effectiveness, indicating that AI systems generate greater operational value when their recommendations complement planners' professional judgment. This supports the view of AI as an augmentative rather than substitutive technology in complex decision-making contexts (Jarrahi, 2018; Makarius et al., 2020). Finally, the study reveals that task complexity significantly moderates the relationship between planner trust and planning effectiveness. Under conditions of high uncertainty and interdependence, trust in AI systems becomes more influential in shaping planning outcomes. This finding is consistent with decision-making research suggesting that reliance on decision support systems increases as task complexity rises (Bonaccio et al., 2010; Rai et al., 2020). Overall, the study concludes that AI-enabled distribution planning is most effective when AI systems are transparent, interpretable, trusted, and aligned with human judgment, particularly in complex retail environments.

5.2. Theoretical Implications

This study makes several important theoretical contributions to distribution science, operations management, and information systems literature. First, it advances existing research by adopting a socio-technical perspective on AI-enabled distribution planning. By explicitly integrating STS theory with Human–AI Interaction and Trust in Automation theories, the study responds to calls for more human-centered and behaviorally grounded explanations of AI effectiveness in organizational contexts (Baxter & Sommerville, 2011; Trist & Bamforth, 1951; Benbya et al., 2020).

Second, the study contributes to the growing literature on human–AI collaboration by empirically demonstrating that trust serves as a central mediating mechanism linking AI system characteristics to operational performance outcomes. While prior research has conceptually emphasized the importance of trust, empirical evidence in distribution and operations contexts has remained limited (Faraj et al., 2018; Glikson & Woolley, 2020). This study helps bridge that gap.

Third, by incorporating task complexity as a moderating

variable, the study extends existing models of AI-supported decision-making by explicitly accounting for contextual contingencies. This finding aligns with calls for more context-sensitive AI research that recognizes the varying effectiveness of intelligent systems across task environments (Dwivedi et al., 2021; Teece, 2018).

5.3. Managerial Implications

The findings offer several actionable insights for managers and practitioners in retail and distribution-intensive industries. First, organizations should prioritize the development and deployment of transparent and interpretable AI systems. Investments in explainable AI features can significantly enhance planner trust and improve the effectiveness of AI-supported planning decisions (Shin, 2021; Floridi et al., 2018; Mittelstadt et al., 2016).

Second, managers should foster human–AI decision alignment by involving planners in AI system design, validation, and continuous improvement processes. Training programs that enhance planners' understanding of AI outputs can further strengthen alignment and trust, consistent with research emphasizing AI augmentation over automation (Ransbotham et al., 2018; Makarius et al., 2020).

Third, in highly complex distribution environments, organizations should actively manage trust calibration by clearly communicating AI system capabilities and limitations. Doing so can help prevent both underutilization and overreliance on AI systems, a challenge highlighted in prior automation research (Lee & See, 2004; Parasuraman & Riley, 1997).

5.3.1. Distribution-Related Implications

This study provides several contributions specifically relevant to distribution science. First, the findings highlight that distribution planning effectiveness, including demand allocation, inventory positioning, and coordination across distribution nodes, depends not only on algorithmic accuracy but also on the quality of human–AI collaboration. Second, planner trust in AI systems is shown to be a critical behavioral mechanism influencing how AI-generated distribution plans are evaluated and implemented in practice. Third, the moderating role of task complexity underscores that AI-enabled distribution planning delivers the greatest value in environments characterized by high uncertainty, interdependent distribution networks, and time-sensitive fulfillment requirements. These insights extend distribution science research by demonstrating that effective distribution planning outcomes emerge from the joint optimization of technical decision-support systems and human judgment rather than from technology adoption alone.

5.4. Limitations and Future Research Directions

The advanced level of AI adoption in South Korea may limit direct generalization to contexts with lower technological maturity, highlighting the need for cross-national replication. First, this study relies on a cross-sectional survey design, which limits the ability to draw causal inferences among the constructs. Although the hypothesized relationships are theoretically grounded in Socio-Technical Systems, Human–AI Interaction, and Trust in Automation theories, the empirical findings reflect statistical associations rather than causal effects. Future research could employ longitudinal or experimental designs to establish causal directionality and examine how trust and human–AI collaboration evolves over time.

Second, the study focuses on the retail industry in South Korea, which may limit generalizability. Replicating the model in other industries or institutional contexts would enhance the robustness of the findings and contribute to a more comprehensive understanding of AI-enabled decision-making (Vrontis et al., 2022; Xu et al., 2021).

Third, future research could incorporate objective performance metrics or system-generated data to complement perceptual measures. Researchers may also explore additional moderators, such as organizational AI maturity or governance mechanisms, to further refine socio-technical models of human–AI collaboration (Dwivedi et al., 2021; Floridi et al., 2018). Future studies could complement perceptual assessments with objective performance indicators such as forecast accuracy, inventory turnover, or service-level performance.

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Declarations

Ethics Approval and Consent to Participate

This study involved human participants. Data was collected through a questionnaire survey administered to distribution planning and supply chain professionals. Participation was voluntary, and respondents were assured of anonymity and confidentiality. No personally identifiable information was collected, and the study complied with standard.

Competing Interests / Conflicts of Interest

The author declares that there are no competing interests.

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Author Contributions

Usman Rehman: Conceptualization, Methodology, Formal analysis, Investigation, Data curation, Writing – original draft, Writing – review & editing, Visualization, Supervision, Project administration.

The author has read and approved the final manuscript.

Data Availability Statement

The data that supports the findings of this study are available from the corresponding author upon reasonable request.

Declaration of Generative AI and AI-assisted Technologies in the Writing Process

The author confirms that no generative AI or AI-assisted technologies were used in the preparation of this manuscript.

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