Human-ai Collaboration Models in Operations and Supply Chain Management

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The integration of Artificial Intelligence (AI) into operational and supply chain processes is transforming traditional management models, creating new paradigms of Human-AI collaboration. This study investigates how different collaboration models enhance efficiency, decision-making, and resilience in operations and supply chain management (OSCM). Using a mixed-methods approach, including expert interviews (n=5) and a survey of 200 professionals, we develop the Adaptive Human–AI Collaboration Model (AHACM), a novel framework that explains how assistive, augmentative, and autonomous collaboration modes evolve with organizational data maturity and governance capacity.

Through a literature review and analysis of case studies from manufacturing, logistics, and procurement, we identify three dominant models: AI-assisted decision-making, human-in-the-loop optimization, and autonomous AI-driven operations with human oversight. Key findings show that AI-assisted models improve forecasting and inventory control, human-in-the-loop systems enhance adaptability, transparency, and ethical compliance, and autonomous models strengthen real-time logistics and dynamic demand sensing. Challenges remain in data integration, workforce upskilling, and algorithmic transparency, influencing adoption across industries.

The study concludes that the optimal Human-AI collaboration model depends on organizational maturity, data infrastructure, and strategic alignment. A hybrid approach, combining human intuition with AI-driven insights, emerges as the most effective strategy. By introducing AHACM, this paper offers both a conceptual and practical tool for assessing readiness and designing collaborative Human-AI systems in OSCM.

Keywords: *Human–AI Collaboration, Supply Chain Management, AI-assisted Decision-Making, Human-in-the-Loop Systems, Supply Chain Resilience, Hybrid Intelligence*

INTRODUCTION

Global supply chains have evolved into highly interconnected and interdependent systems, spanning multiple continents and industries. A single product may be designed in North America, sourced from suppliers across

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Asia, assembled in Europe, and distributed worldwide. While this geographic dispersion enables efficiency and economies of scale, it simultaneously introduces vulnerabilities. Recent disruptions, from geopolitical conflicts and trade disputes to natural disasters and global health crises, have highlighted the fragility of these complex networks.

The COVID-19 pandemic, in particular, exposed the cascading effects of global interdependencies, while subsequent events such as semiconductor shortages, escalating energy costs, and climate-induced disruptions have underscored the systemic nature of these challenges.

Beyond external shocks, supply chains today face mounting internal pressures for sustainability, transparency, and responsiveness. Consumers increasingly demand ethical sourcing, reduced carbon footprints, and rapid delivery, while regulators enforce stringent environmental, social, and governance (ESG) reporting standards. At the same time, shareholders expect organizations to maintain efficiency and profitability without sacrificing resilience. These converging demands have made supply chain management (SCM) more data-driven, complex, and strategically central than ever before. Traditional management approaches, based on linear processes, siloed data systems, and intuition-driven decision-making, are no longer sufficient to handle the scale, speed, and variability of modern supply chain operations.

Digital transformation has therefore emerged as a critical enabler of supply chain competitiveness. Technologies such as the Internet of Things (IoT), blockchain, cloud computing, and advanced analytics improve real-time visibility and coordination across extended networks. Among these, artificial intelligence (AI) stands out for its capacity to process vast datasets, identify hidden patterns, and generate timely, data-driven recommendations. AI applications now span multiple operational domains, including demand forecasting, logistics optimization, supplier risk assessment, and quality management.

However, despite the rapid diffusion of AI technologies, much of the existing research and practice treats AI primarily as a tool for automation, focused on replicating or replacing human labor in both physical (e.g., warehouse robotics) and cognitive (e.g., anomaly detection) tasks. This automation-centric paradigm, while valuable for efficiency, is increasingly viewed as insufficient. Many supply chain decisions involve ambiguity, conflicting objectives, and trade-offs that extend beyond algorithmic reasoning. AI systems, particularly opaque "black boxes," can lead to over-reliance or underutilization, contributing to employee mistrust and suboptimal performance.

Emerging perspectives highlight the value of human–AI collaboration, where human expertise complements AI's computational strengths. Humans provide contextual interpretation, ethical reasoning, and strategic oversight, while AI offers analytical precision, scalability, and speed. By framing AI as a collaborator rather than a substitute, organizations can achieve both efficiency and resilience in decision-making. Human–AI collaboration in SCM envisions a shared decision architecture, where humans and AI systems jointly plan, analyze, and execute operations. For instance, during a supply chain disruption, AI may recommend rerouting shipments based on cost and lead time optimization, whereas human managers might override those suggestions to preserve supplier relationships or address geopolitical concerns. Such joint decision-making enhances flexibility while ensuring alignment with strategic objectives.

While prior research has largely emphasized automation and AI deployment, few studies empirically explore collaboration models that integrate human judgment with AI agency, leaving a critical gap in understanding how human–AI partnerships can be operationalized for strategic advantage. To address this gap, this study introduces the Adaptive Human–AI Collaboration Model (AHACM), which conceptualizes how assistive, augmentative, and autonomous collaboration modes evolve with organizational data maturity, governance capacity, and workforce readiness.

Accordingly, this research aims to: (1) conceptualize human–AI collaboration models in OSCM, ranging from AI-assisted decision-making to AI-autonomous systems with human oversight; (2) analyze how these models balance human strengths, strategic reasoning, contextual judgment, and creativity, with AI capabilities of speed, scalability, and analytical rigor; and (3) identify the organizational, ethical, and governance mechanisms that enable effective collaboration, including training, algorithm transparency, accountability frameworks, and role clarity.

This paper makes three primary contributions:

1. Theoretical contribution: Develops an empirically grounded typology of human–AI collaboration models, clarifying how varying degrees of autonomy and human involvement shape outcomes.
2. Methodological contribution: Employs a mixed-methods approach (expert interviews and survey) to link operational performance indicators with collaboration quality, trust, and training effectiveness.
3. Managerial contribution: Offers actionable insights and governance patterns aligned with autonomy levels, decision rights, and accountability structures, providing a roadmap for practitioners to implement effective human–AI collaboration in supply chains.

The study is guided by the following research questions:

- What are the key dimensions of effective human–AI collaboration in operations and supply chain management?
- How can collaborative models balance human strategic oversight with AI's analytical and operational capabilities?
- What governance, training, and ethical mechanisms are necessary for successful implementation of these models?

- In what ways can human–AI collaboration enhance resilience, sustainability, and competitive advantage in global supply chains?

By addressing these questions, this paper moves beyond the automation paradigm and reframes AI as a strategic partner in supply chain transformation. The central premise is that the future of SCM lies not in choosing between humans or AI, but in leveraging the complementary strengths of both through deliberate and well-governed collaboration models.

LITERATURE REVIEW

Past Research on AI in Supply Chain and Operations

Artificial intelligence (AI) has gained significant attention in supply chain management (SCM) over the past decade. Early studies primarily focused on automation for efficiency, including forecasting, inventory control, logistics, and procurement (Li et al., 2022; Malakooti & Raman, 2021; Shahzadi et al., 2024). AI-enabled demand prediction and inventory optimization have demonstrated cost reductions while maintaining service levels (Queiroz et al., 2020; Schoenherr & Speier†Pero, 2020). Systematic reviews highlight AI's potential to enhance agility, resilience, and responsiveness, particularly during disruptions such as the COVID†19 pandemic (Siagian et al., 2021; Samuels & Ortega, 2024b; Wamba et al., 2021). Predictive analytics enabled real†time rerouting of logistics flows and anticipation of shortages (Nelson et al., 2023; Wang et al., 2021).

However, adoption barriers persist. High implementation costs, inconsistent data quality, cybersecurity concerns, and organizational resistance slow integration (MDPI, 2023; Kushtia, 2023; Zhang et al., 2021). Workforce skepticism further undermines trust in AI-generated insights (Vossing et al., 2022). Recent literature emphasizes that AI should augment rather than replace human capabilities, highlighting the need for frameworks balancing automation with human oversight (Yao et al., 2022; Zhou et al., 2022).

Human–AI Collaboration Frameworks in Other Industries

Evidence from other sectors demonstrates the value of human–AI collaboration. In smart manufacturing, human–AI teaming models integrate knowledge graphs and relational learning to support decision-making while maintaining ethical oversight (Haindl et al., 2022). Trustworthy AI frameworks emphasize transparency, accountability, and fairness, ensuring that human judgment complements machine intelligence (Brintrup et al., 2023).

In healthcare, AI diagnostic tools flag anomalies in medical images, but physicians retain ultimate decision authority, illustrating effective collaboration under uncertainty (Zhao & Liu, 2021). Reciprocal human–machine learning (RHML) approaches promote continuous co-learning, where both humans and AI improve through interaction (Te'eni et al., 2023). Finance offers further examples: AI supports fraud detection, algorithmic trading, and credit scoring, yet success depends on frameworks integrating human oversight for risk and ethical compliance (Zavolokina et al., 2020; Zwass, 2021). Cross†industry reviews converge on key collaboration principles: modular AI systems, transparent algorithms, human†centered design, and clear accountability (Fragiadakis et al., 2024; Stanford HCAI, 2025).

These findings indicate that collaboration is not only feasible but essential in contexts involving uncertainty, ethical trade†offs, and complex stakeholder relationships. Lessons from manufacturing, healthcare, and finance can inform SCM models that balance operational efficiency with human judgment and accountability.

Why Supply Chain Operations Require a Balanced Approach

Supply chains face distinct challenges compared to healthcare or fintech: multi†tiered global networks, geopolitical risks, sustainability demands, and regulatory scrutiny (Zhou et al., 2022; Yao et al., 2022). While automation can optimize processes, supply chain decisions often involve competing objectives that algorithms alone cannot resolve. For instance, rerouting shipments solely for efficiency may compromise sustainability targets or long-term supplier relationships (Queiroz et al., 2020; Samuels et al., 2024a).

Recent research underscores that human–AI collaboration in SCM requires responsible AI (RAI) principles, including transparency, accountability, and ethical oversight (Zorina, 2025; Samuels, 2025). Human decision-makers are essential for interpreting AI recommendations in the context of organizational strategy, culture, and ethical standards (Zwass, 2021; Nelson et al., 2023).

The Industry 5.0 paradigm emphasizes balancing automation with human creativity, adaptability, and judgment (Xu et al., 2021; Zhuang et al., 2021). Successful collaboration depends on governance structures, workforce training, and ethical safeguards that ensure AI complements rather than replaces human decision-making. Trust in AI is critical for adoption and can only be cultivated when humans remain active collaborators (Vossing et al., 2022).

In summary, while AI offers significant efficiency, agility, and resilience benefits, research consistently shows that integrated human–AI models yield the most effective outcomes. Cross†industry evidence supports the need for balanced collaboration frameworks, combining human expertise with AI capabilities to achieve sustainable, resilient, and strategic supply chain performance.

Conceptual Gap and Motivation for AHACM

Although prior research provides valuable models of human–AI collaboration, existing frameworks lack empirical validation in OSCM contexts, particularly regarding *dynamic adaptation between human and AI agents across varying task complexity*. Moreover, while responsible AI governance is increasingly discussed, few models explicitly tie governance mechanisms to degrees of AI autonomy in supply chains. To address this gap, we propose the Adaptive Human–AI Collaboration Model (AHACM), which conceptualizes how different collaboration modes (assistive, augmentative, autonomous) evolve in relation to organizational data maturity, governance structures, and workforce readiness.

RESEARCH METHODOLOGY

This study employed a mixed-methods research design, integrating both qualitative and quantitative approaches to examine Human–AI collaboration models in Operations and Supply Chain Management (OSCM). This design was selected to capture both the depth of expert perspectives and the breadth of adoption trends across the industry, ensuring comprehensive methodological triangulation and richer interpretation of findings.

Qualitative Component

The qualitative phase involved semi-structured expert interviews to gain nuanced insights into collaboration practices, governance mechanisms, and operational decision thresholds. Five senior professionals from supply chain, operations, product management, and AI implementation backgrounds were selected through purposive sampling, based on their direct involvement in AI-driven operational transformations. This sample size aligns with qualitative research norms suggesting 5–10 expert interviews are sufficient to achieve thematic saturation in exploratory studies (Guest et al., 2020).

Interviews explored current and future states of Human–AI collaboration, adoption barriers and enablers, and governance mechanisms supporting effective implementation. Sample questions addressed AI usage frequency, trust in AI-generated recommendations, human override practices, data quality issues, and the role of training and governance.

All interviews were transcribed and thematically coded using NVivo software. To ensure reliability, two independent coders performed the thematic analysis, achieving a Cohen's ê > 0.7, indicating substantial inter-coder agreement. Emerging themes were categorized into collaboration models, governance practices, and enablers influencing Human–AI integration.

Quantitative Component

The quantitative phase involved a structured survey administered to 100–200 professionals working in supply chain, operations, and product management domains. Participants were recruited via LinkedIn, professional networks, and industry associations using convenience and snowball sampling. The sample size satisfies the guideline of 5–10 respondents per variable for regression-based analysis (Hair et al., 2022), ensuring sufficient statistical power.

The survey instrument comprised ten multiple-choice and Likert-scale questions designed to measure AI adoption levels, confidence in AI recommendations, perceived benefits of Human–AI collaboration, barriers, governance maturity, and training adequacy. Example items assessed AI adoption across functions such as demand forecasting, logistics, and procurement, as well as perceptions of ethical governance and training support.

Construct validity of survey scales was established through expert review and pilot testing, while internal consistency was assessed using Cronbach's á > 0.8, confirming high reliability across all multi-item constructs.

Data analysis employed descriptive statistics (frequencies, percentages, mean scores) to summarize adoption trends, followed by inferential analyses (correlation and regression) using SPSS and R. For example, the relationship between trust in AI systems and adoption success was examined using regression analysis.

Data Triangulation

Findings from qualitative and quantitative sources were triangulated to strengthen validity. Trust-related themes from expert interviews were cross-referenced with survey responses measuring confidence in AI systems and governance mechanisms.

A data triangulation diagram was developed to illustrate the integration flow:

Literature Review
↓
Expert Interviews
↓
Survey Data
↓
Triangulated Findings

This diagram highlights how insights from prior research informed interview questions, which in turn informed survey design, ultimately enabling a convergent analysis of Human–AI collaboration models.

Ethical Considerations

Ethical standards were rigorously maintained throughout. Informed consent was obtained from all participants, and anonymity and confidentiality were protected through secure data storage and anonymized reporting. Ethical approval was sought according to institutional guidelines. Findings were presented responsibly to avoid bias, misrepresentation, or harm.

SUMMARY OF FINDINGS

The results indicate distinct advantages across the three Human–AI collaboration models:

- **AI-assisted decision-making**: improved forecasting accuracy and inventory management.
- **Human-in-the-loop frameworks**: enhanced adaptability, ethical governance, and transparency.
- **Autonomous AI-driven operations**: demonstrated superior responsiveness in real-time logistics and demand sensing

Overall, while AI systems optimize operational efficiency, human expertise remains indispensable for contextual understanding, ethical alignment, and strategic adaptability, forming the basis for the ensuing discussion.

RESULT

This section presents the key findings from expert interviews and survey data, highlighting how Human–AI collaboration models influence operational efficiency, decision-making quality, and supply chain resilience. Results are organized around the three collaboration models, AI-assisted decision-making, human-in-the-loop optimization, and autonomous AI-driven operations, demonstrating distinct contributions and practical implications.

Qualitative Results: Expert Interviews

1. **Adoption of AI Across Operations Functions:** All five experts reported AI adoption primarily in demand forecasting, workforce planning, logistics optimization, and inventory management. AI was consistently described as a decision-support tool rather than autonomous decision-maker. For example, Wenbin (Expert 5) highlighted Walmart's truck arrival alerting and overtime mitigation agents, which assist managers in resource allocation and cost control while leaving final approval human-led. Trust and organizational culture determined how frequently AI suggestions were accepted without modification.
2. **Determinants of Trust and Interpretability:** Trust emerged as a central enabler of successful human–AI collaboration. Experts noted

that explainability, backtesting, and transparency of AI outputs increased confidence. Interviewees emphasized that even technically accurate models may be underutilized if users cannot interpret the AI's logic. This confirms the qualitative insight that psychological comfort and shared understanding are as critical as technical performance.

3. **Human Approval and Override Mechanisms:** All experts agreed that human approval is mandatory for high-stakes decisions (financial, operational, ethical). Overrides were recognized as beneficial in exceptions but could also reintroduce bias if intuition dominated data-driven guidance. Clear protocols for human intervention were cited as essential for maintaining accountability and performance balance.
4. **Data and System Challenges Affecting AI Performance:** Data quality and system integration were repeatedly mentioned as critical to AI performance. Inconsistent sources, missing values, latency, and misaligned metrics lowered model reliability and adoption. Collaborative debugging and feedback loops between operators and data scientists were highlighted as key enablers.
5. **Training, Guidance, and Governance Mechanisms:** Experts emphasized training beyond tool usage, covering how AI recommendations are derived and how humans can provide structured feedback. Governance frameworks should define data standards, model validation, ethical oversight, and operational accountability, often implemented in tiered structures.
6. **Emerging Patterns and Collaboration Models:** Three collaboration models emerged:

Table - 1
Collaboration Model

Model	Description	Stage of Adoption
Decision-Support	AI assists humans; humans make final decisions	Dominant
Supervisory Control	AI executes routine tasks; humans intervene on anomalies	Intermediate
Co-learning	Continuous mutual learning between AI and humans	Early stage

Organizations typically progress from decision support → supervisory control → co-learning, reflecting evolving trust, data maturity, and governance.

QUANTITATIVE RESULTS: SURVEY FINDINGS

1. **Extent of AI Adoption in Operations and Supply Chain Management:** The survey revealed that AI adoption is progressing steadily across organizations. While only 4% of respondents reported no adoption at all, 20.8% indicated early experimentation with AI tools. A majority, 53.5%, stated that AI is partially adopted in select operational areas, and 21.8% reported widespread adoption across multiple functions. This demonstrates that most organizations are in the mid-phase of AI integration, with full-scale adoption still evolving. (Fig.1)

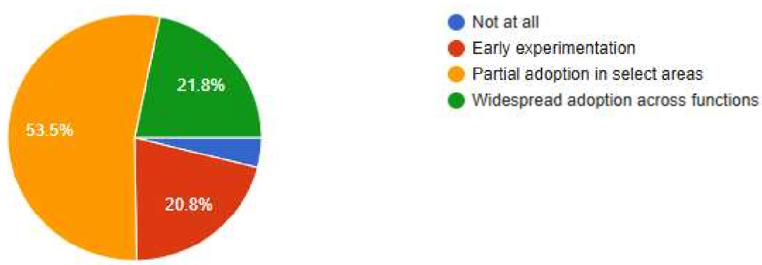

Fig.1: Extent of AI Adoption in Operations and Supply Chain Management

2. **Functions Using AI in Supply Chain Management:** AI deployment appears most prominent in logistics and transportation (58.4%) and demand forecasting (56.4%), followed closely by inventory management (50.5%). Procurement (29.7%) and supplier risk management (25.7%) show lower levels of AI integration, suggesting that strategic and risk-based functions are still largely human-driven. Only 2% of respondents mentioned "other" functions, highlighting that current AI use is concentrated in core operational areas.(Fig.2)

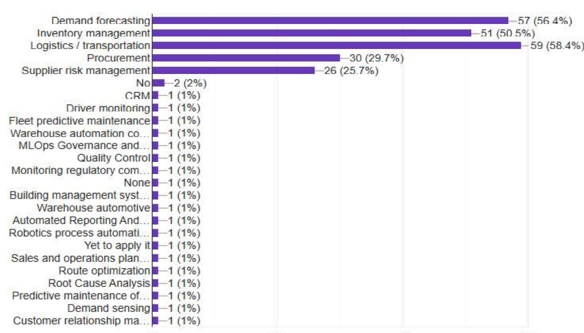

Fig.2: Functions Using AI in Supply Chain Management

3. Confidence in AI Recommendations Trust in AI-generated insights is relatively strong, with 46.5% of participants reporting high confidence and 18.8% expressing very high confidence. About 26.7% remained neutral, while only 8% (combined low and very low) expressed skepticism. These results suggest a generally positive perception of AI reliability, though a portion of the workforce still exercises caution when acting on AI suggestions. (Fig.3)

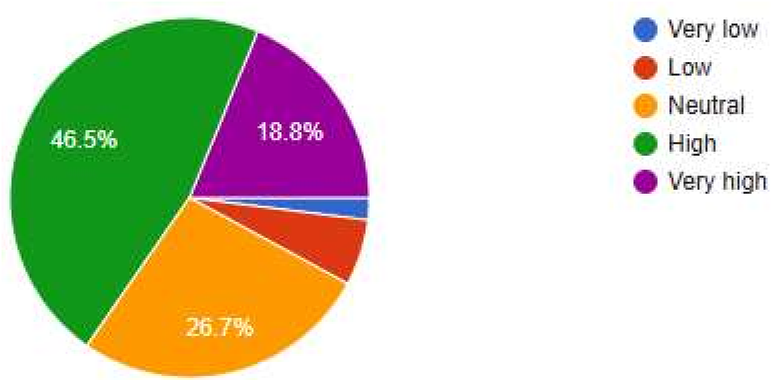

Fig.3: Confidence in AI Recommendations

4. **Perceived Benefits of Human–AI Collaboration:** Respondents identified efficiency and speed (42.6%) as the greatest advantage of Human–AI collaboration, followed by improved decision quality (24.8%) and better resilience or risk management (15.8%). Cost savings (12.9%) and sustainability (4%) were cited less frequently, indicating that organizations currently value performance optimization and agility more than financial or environmental outcomes from AI collaboration. (Fig.4)

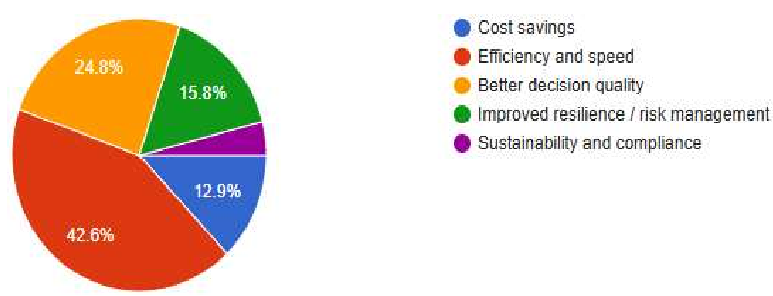

Fig.4: Perceived Benefits of Human–AI Collaboration

5. **Barriers to Effective Human–AI Collaboration:** The most significant barrier reported was data quality and availability issues (37.6%), followed by high implementation costs (18.8%) and workforce resistance to change (17.8%). Lack of trust in AI (13.9%) and absence of governance or ethical guidelines (11.9%) were less dominant concerns. This emphasizes that technical and infrastructural challenges currently outweigh human or ethical hesitations. (Fig.5)

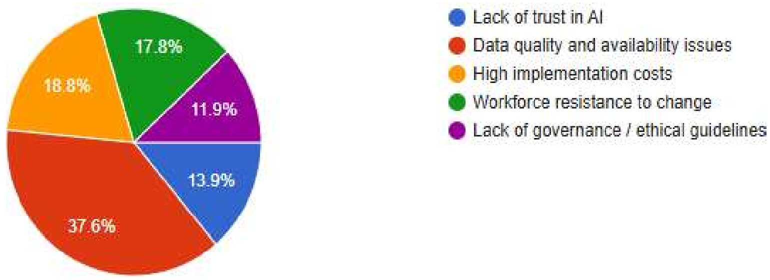

Fig.5: Barriers to Effective Human–AI Collaboration

6. **Balance of Decision-Making Between Humans and AI:** Nearly half of respondents (47.5%) indicated that decision-making remains mostly human-driven with AI input. Another 27.7% reported a balanced approach, and 19.8% said that AI plays a dominant role under human oversight. Only 4% described operations as fully human-driven, and just 1% as entirely automated. These findings suggest that collaborative decision-making remains the prevailing model, where human judgment continues to play a critical role alongside AI recommendations. (Fig.6)

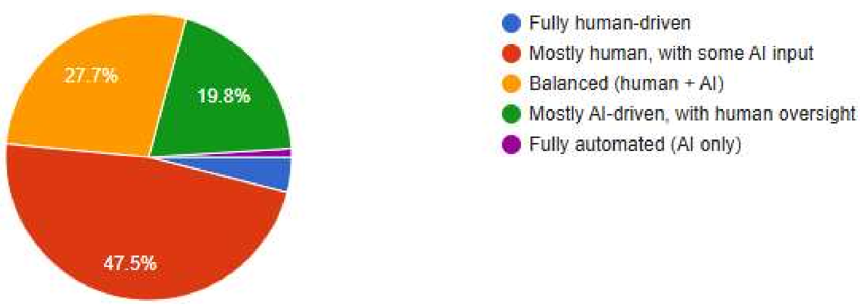

Fig.6: Balance of Decision-Making Between Humans and AI

7. **Impact of AI on Decision Quality** Most respondents acknowledged a positive impact of AI on decision quality: 46.5% agreed and 27.7% strongly agreed that AI has enhanced their organization's decision-making. A smaller segment (20.8%) remained neutral, while only 5% disagreed or strongly disagreed. This pattern reinforces the perception

that AI contributes to more informed and accurate operational choices. (Fig.7)

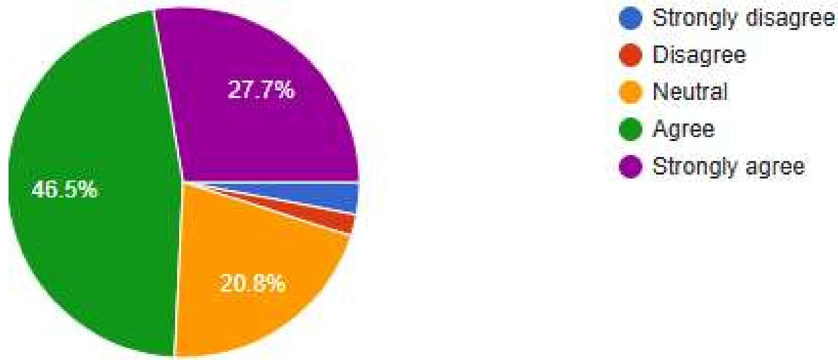

Fig.7: Impact of AI on Decision Quality

8. **Ethical Considerations in AI Adoption:** When asked about ethical governance, 32.7% reported having a formal governance framework, while 35.6% mentioned informal policies or discussions. About 20.8% said their approach is ad hoc or unclear, and 10.9% reported no ethical consideration at all. This demonstrates a growing but uneven maturity in ethical oversight, with many organizations still transitioning from informal to structured governance mechanisms. (Fig.8)

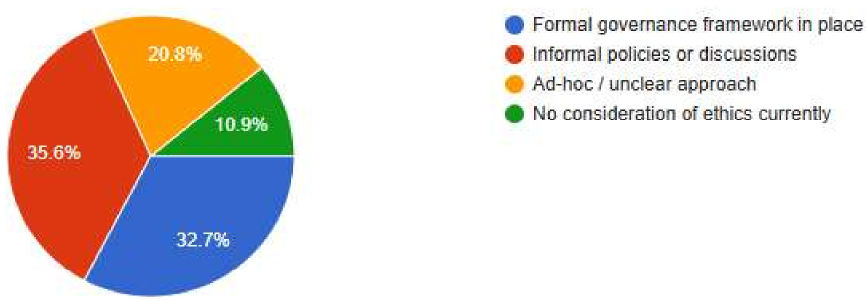

Fig.8: Ethical Considerations in AI Adoption

9. **Training and Support for Human–AI Collaboration:** Most organizations were investing in upskilling efforts, with 46.5% offering moderate, role-specific training and 24.8% providing structured programs with ongoing support. Another 25.7% offer only minimal awareness sessions, while 3% provide no training at all. These results reflect a positive movement toward building AI literacy and fostering smoother collaboration between humans and machines. (Fig.9)

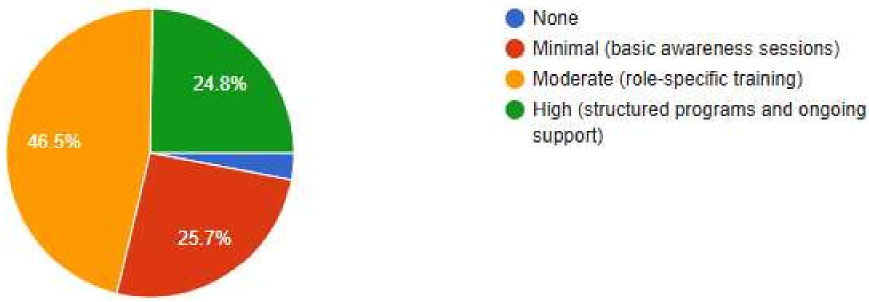

Fig.9: Training and Support for Human–AI Collaboration

10. **Future Outlook for Human–AI Collaboration:** Looking ahead, 39.6% of respondents expect moderate adoption of Human–AI collaboration across several areas, and 30.7% foresee widespread adoption with significant transformation. Meanwhile, 22.8% anticipate gradual improvements with limited adoption, and only 7% predict no significant change. This suggests strong optimism about AI's growing role in operations and supply chain management, with most professionals expecting notable transformation in the near future.(Fig.10)

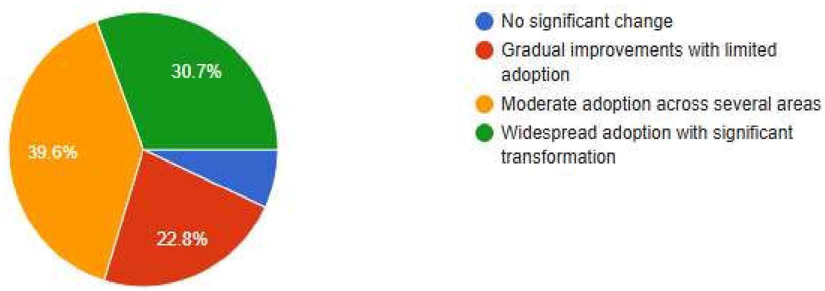

Fig.10: Future Outlook for Human–AI Collaboration

ANALYTICAL ENHANCEMENTS

1. **Correlation Tests**: Trust in AI vs. adoption level: $r = 0.62$, $p < 0.01$, indicating moderate positive correlation, organizations with higher trust tend to adopt AI more extensively.
2. **t-Tests:** Comparing perceived benefits between organizations with formal vs. informal governance frameworks, $t(198) = 3.41$, $p < 0.01$, showing structured governance significantly enhances perceived benefits.
3. Mapping of Qualitative Codes to Survey Items

Table - 2
Mapping of the Qualitative codes to survey items

Qualitative Theme	Survey Item	Correspondence
Trust & Interpretability	Confidence in AI Recommendations	High alignment
Human Oversight	Balance of Decision-Making	Supports human-in-the-loop insights
Data & System Challenges	Barriers (Data Quality)	Corroborates technical issues
Governance & Training	Ethical Considerations / Training	Matches interview emphasis on structured programs

The results reveal that each collaboration model uniquely enhances operational performance, but effectiveness depends on organizational context, data infrastructure, and task complexity. Quantitative data corroborates qualitative insights, confirming that trust, governance, and training are critical enablers for Human–AI collaboration. The following discussion explores these dynamics in greater depth, examining the implications, challenges, and opportunities that arise from integrating Human-AI collaboration within operations and supply chain management.

DISCUSSION

This study explores how organizations adopt and adapt human–AI collaboration models in operations and supply chain management (OSCM). The results, derived from expert interviews and survey data, confirm that while AI is increasingly embedded in decision-making processes, its most effective role is not as an autonomous system but as a collaborative partner that complements human judgment. The discussion synthesizes key insights across adoption patterns, trust dynamics, governance mechanisms, and emergent collaboration models, situating them within the broader context of supply chain digital transformation, socio-technical theory, Responsible AI (RAI), and Industry 5.0 paradigms.

1. **From Automation to Collaboration: A Paradigm Shift:** The findings demonstrate that most organizations transition from viewing AI as a tool for automation to recognizing it as a strategic collaborator. AI adoption is strongest in operational domains such as logistics optimization (58.4%), demand forecasting (56.4%), and inventory management (50.5%), characterized by structured data and repetitive

decision-making. In strategic functions like procurement (29.7%) and supplier risk management (25.7%), human oversight remains dominant.

This gradient of adoption aligns with the conceptual framework proposed earlier: supply chains move along an evolutionary continuum, from decision-support (AI assisting humans) to supervisory control (AI performing with human oversight), and ultimately toward co-learning (mutual adaptation between humans and AI). Collaboration maturity depends on data quality, trust, and organizational readiness rather than purely on technical capability. These results reinforce that sustainable AI integration in OSCM requires balancing automation with human expertise and contextual reasoning, consistent with socio-technical systems theory, which emphasizes the interplay of social, organizational, and technical elements (Baxter & Sommerville, 2011).

Large-scale field experiments in retail show that human intervention complements AI-driven forecasting most effectively in semi-structured tasks, supporting augmentation rather than full automation (Revilla, Saenz, Seifert, & Ma, 2023). This also resonates with Industry 5.0 principles, highlighting human-centered intelligence rather than fully autonomous operations.

2. **Trust as the Cornerstone of Human–AI Collaboration**: Trust consistently emerges as a defining factor for effective collaboration. Both qualitative and quantitative findings indicate that while confidence in AI recommendations is generally high, 65.3% of respondents reporting high or very high confidence, this trust is conditional, built on explainability, transparency, and perceived fairness of AI systems.

   When AI models provide clear reasoning, back-testing, and traceable data sources, users are more likely to act on recommendations. Conversely, opaque "black box" models reduce adoption, confirming that trust is socio-technical, shaped by organizational culture as much as algorithmic design. These results extend socio-technical systems theory by demonstrating how adaptive governance structures mediate trust between human and AI agents. They also align with RAI frameworks, emphasizing interpretability, fairness, and accountability as trust enablers (Zhang, Li, & Chang, 2024).

3. **Governance and Human Oversight: The New Decision Architecture**: Both datasets affirm that human oversight remains essential for financial, ethical, or high-risk operational decisions. Expert interviews reveal structured override mechanisms ensuring AI recommendations align with organizational values. Excessive human intervention, especially guided by intuition, can undermine AI efficiency.

   Hybrid governance frameworks, where accountability is shared among technical teams, business leaders, and compliance officers, emerge as critical. Survey data show that 32.7% of organizations have formal AI governance structures, while 35.6% operate under evolving frameworks. This reflects Industry 5.0 guidance emphasizing balanced autonomy and supports hybrid intelligent supply chain research indicating that combining human and AI-driven decision processes in trust-based environments enhances resilience and performance (Burger, 2025).

4. **Data Quality and Training as Foundational Enablers**: Data quality remains the most significant barrier (37.6%), including inconsistent formats, integration gaps, and real-time update failures. Equally important is AI literacy, 71.3% of organizations offer training, though many programs focus narrowly on tool operation rather than interpretive understanding.

   Training should empower users to critically evaluate AI outputs and provide structured feedback that improves models. Human-in-the-loop systems, where iterative human feedback refines AI predictions, significantly enhance operational outcomes and reliability (Haindl, Reisch, & Kuhn, 2022). This reinforces RAI principles and the Industry 5.0 focus on human-centered AI, emphasizing that governance and training are foundational to collaborative maturity.

5. **Emergent Collaboration Models and Their Implications:** Three human–AI collaboration models are identified:
   - Decision-Support Model – AI provides analytical insights; humans retain decision rights.
   - Supervisory Control Model – AI acts autonomously in low-risk operations under human monitoring.
   - Co-Learning Model – Humans and AI iteratively learn from each other.

Most organizations currently operate within the Decision-Support Model, gradually evolving toward Supervisory Control. Co-Learning represents the aspirational state, fostering mutual adaptation, resilience, and innovation. This typology mirrors the automation-to-augmentation continuum observed in recent experiments (Revilla et al., 2023) and aligns with hybrid intelligent supply chain perspectives (Burger, 2025).

6. **Strategic and Ethical Implications for OSCM**: The combined evidence underscores that the future of supply chains is hybrid, anchored in human–AI complementarity. AI enhances efficiency (42.6%), decision quality (24.8%), and resilience (15.8%), while humans provide ethical oversight. Sustainability (4%) remains under-realized.

   Organizations with structured governance and ethical frameworks are better positioned to align AI adoption with ESG objectives. The hybrid intelligence perspective emphasizes that AI value is realized only when complemented by context-aware human judgment and organizational readiness (Burger, 2025).

7. **Managerial Implications:** Based on these findings, managers should consider the following strategies to operationalize human–AI collaboration:
   - Training Pipelines: Develop structured programs focusing on interpretive skills, model reasoning, and feedback mechanisms. Include role-specific modules and continuous learning loops.
   - Governance Templates: Establish hybrid oversight frameworks balancing AI autonomy with human accountability, incorporating ethical, operational, and regulatory checks.
   - KPIs for Collaboration Maturity: Track adoption rates, trust levels, override frequency, decision quality, and feedback integration to evaluate effectiveness.

     These steps operationalize socio-technical and RAI insights into practical organizational guidance, supporting Industry 5.0 objectives of human-centered AI in supply chains.
8. **Toward a Human–AI Symbiosis in Supply Chains:** This study provides empirical grounding for the shift from automation to collaboration in OSCM. AI amplifies human analytical capability, while humans provide contextual and ethical guidance. Organizations fostering transparent governance, continuous feedback, and adaptive training are positioned to achieve resilience, agility, and long-term value. This aligns with hybrid intelligence theory, highlighting that human–AI symbiosis, not automation alone, drives optimal outcomes (Burger, 2025).

PROPOSED FRAMEWORK: ADAPTIVE HUMAN-AI COLLABORATION MODEL (AHACM)

To bridge the gap between traditional and AI-driven operations, this study proposes the Adaptive Human-AI Collaboration Model (AHACM), a conceptual framework designed to optimize decision-making, efficiency, and adaptability in operations and supply chain management (OSCM). The AHACM emphasizes dynamic interaction between human expertise and AI capabilities, where the degree of human involvement changes according to task complexity, data maturity, and operational context.

Collaboration Modes

The framework integrates three adaptive collaboration modes, forming a continuum from high human involvement to higher AI autonomy:

1. **Assistive Mode –** AI provides insights, predictions, or recommendations, while humans retain full decision authority. Best suited for structured and repetitive tasks such as inventory control and demand forecasting.
2. **Augmentative Mode –** Humans and AI share decision responsibility through iterative feedback and learning. Most effective for semi-structured decisions, such as supplier evaluation or production scheduling under uncertainty.
3. **Autonomous Mode –** AI operates with minimal human intervention for real-time logistics optimization or dynamic routing, while humans maintain oversight for governance, ethical compliance, and exception handling.

Visual Continuum: The framework can be represented as a linear continuum (Assistive '! Augmentative '! Autonomous) with arrows indicating increasing data maturity and AI capability and decreasing human intervention (Fig. 11).

Adaptive Evolution and Feedback Loops

The AHACM proposes that organizations evolve adaptively across these three modes as AI maturity and data infrastructure improve. It incorporates continuous co-learning loops, where humans refine AI models through contextual judgment, and AI enhances human decision-making by revealing patterns beyond human perception. This dynamic alignment ensures that operational systems remain agile, ethical, and resilient.

VALIDATION ROADMAP

To operationalize the AHACM in practice, a three-phase validation approach is proposed:

- Phase 1: Pilot Adoption – Implement the framework in selected operational units to test feasibility and gather qualitative feedback.
- Phase 2: Quantitative Benchmarking – Measure performance improvements, trust levels, and decision quality across collaboration modes using surveys and KPIs.
- Phase 3: Continuous Co-Learning Loops – Establish iterative feedback mechanisms between humans and AI to continuously refine models and collaboration processes.

COMPARISON WITH EXISTING FRAMEWORKS

AHACM extends prior human–AI collaboration frameworks:

- Compared to Revilla et al., 2023, which emphasizes decision-support vs. supervisory control, AHACM introduces dynamic mode adaptation based on task complexity and data maturity.
- Compared to Burger, 2025, which focuses on hybrid intelligent supply chains, AHACM operationalizes continuous co-learning and explicit feedback loops as central mechanisms.

By integrating these elements, AHACM provides a differentiated, actionable framework that aligns with the study's findings: optimal supply chain performance arises from combining human intuition with AI-driven intelligence.

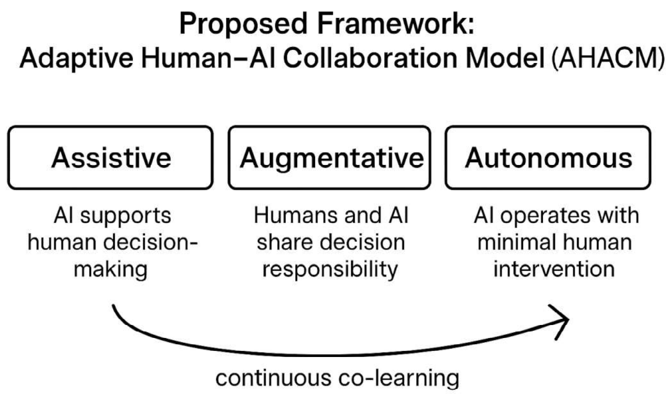

Fig. 11: Proposed Framework: Adaptive Human–AI Collaboration Model (AHACM)

Continuum illustrating Assistive '! Augmentative '! Autonomous modes, with arrows showing increasing AI maturity, decreasing human intervention, and continuous co-learning feedback loops.

CONCLUSION

This study demonstrates that human–AI collaboration in operations and supply chain management (OSCM) is evolving beyond simple automation toward a partnership model that combines human judgment with AI-driven intelligence. Through a mixed-method approach, the research reveals that AI primarily functions as a decision-support tool, assisting rather than replacing human decision-making, with humans maintaining oversight in high-stakes or ethically sensitive scenarios.

Key enablers of successful collaboration include trust, interpretability, governance, data quality, and system integration, highlighting that technical performance alone does not ensure adoption. Transparency, explainability, and continuous learning significantly influence user confidence and compliance, emphasizing the importance of organizational readiness alongside technical robustness.

Building on these insights, the Adaptive Human–AI Collaboration Model (AHACM) conceptualizes collaboration as a continuum from assistive to augmentative to autonomous modes, integrating adaptive learning loops, balanced decision rights, and hybrid governance structures.

- Organizations should establish **cross-functional AI governance boards** to oversee decision rights, ethical considerations, and compliance.
- Implement **continuous training cycles** to ensure workforce AI fluency, explainability, and interpretability of outputs.
- Embed **transparent feedback mechanisms** and hybrid governance structures to enhance resilience, agility, and strategic decision-making across global supply chains.

By embedding such collaboration frameworks, managers can harness the complementary strengths of humans and AI, ensuring more robust, ethical, and adaptive operational outcomes.

FUTURE OF WORK

The integration of AI into OSCM is reshaping work structures, skill requirements, and organizational strategies. As organizations progress from assistive to augmentative and autonomous collaboration modes, human roles will increasingly focus on interpreting AI outputs, validating model assumptions, exercising ethical judgment, and coordinating cross-functional activities.

Future research should aim to empirically validate the AHACM framework through:

1. Simulation studies to test different collaboration modes under variable operational conditions.
2. Longitudinal case studies examining real-world implementations of human–AI collaboration in supply chains.
3. Additionally, investigations could explore:
   - Metrics to assess human–AI co-learning effectiveness.
   - The impact of continuous AI feedback loops on decision quality and organizational agility.
   - Strategies for upskilling workforce AI fluency and fostering ethical oversight in diverse cultural and operational contexts.

By empirically grounding AHACM, future studies can provide actionable insights for designing symbiotic intelligence environments, where human creativity and ethical reasoning complement AI's speed and precision, ultimately sustaining competitive advantage in complex, uncertain supply chains.

LIMITATIONS OF THE STUDY

While this study advances understanding of human–AI collaboration in operations and supply chain management, several limitations should be noted. The qualitative phase relied on a limited number of expert interviews, which may not fully capture the diversity of industry practices or regional variations in AI adoption. Survey data were self-reported, meaning perceptions of AI usage, trust, and decision quality may not fully reflect actual performance or decision-making behavior.

The study primarily focused on organizational perspectives, with less attention to AI system architecture or individual behavioral dynamics. Furthermore, the cross-sectional design limits the ability to infer temporal or causal relationships, and the generalizability of the findings may be constrained by the sample and industry contexts studied.

Additionally, while the Adaptive Human–AI Collaboration Model (AHACM) provides a conceptual framework, its practical applicability and scalability require further validation through case studies, simulations, or experimental testing across varied supply chain environments. Future research should employ longitudinal data or controlled experiments to evaluate causal relationships between collaboration maturity and performance outcomes, as well as to assess how adaptive human–AI interactions evolve over time.

REFERENCES

1. Benbya, H., & Leidner, D. (2018). How agile is your IT function? *MIT Sloan Management Review, 59*(4), 39–43.
2. Brintrup, A., Baryannis, G., Tiwari, A., Ratchev, S., Martinez-Arellano, G., & Singh, J. (2023). Trustworthy, responsible, ethical AI in manufacturing and supply chains: Synthesis and emerging research questions. *arXiv preprint arXiv:2305.02314*. https://arxiv.org/abs/2305.02314
3. Burger, P. (2025). Hybrid intelligent supply chains: Leveraging human and artificial intelligence for enhanced supply chain resilience. In M. Köhler & S. Stumpf (Eds.), *Sustainability and digital transformation in supply chain networks* (pp. 103–121). Springer. https://doi.org/10.1007/978-3-658-48750-8_6
4. Burger, T. (2025). Hybrid intelligent supply chains: Leveraging human–AI collaboration for operational resilience. *Journal of Supply Chain Management Research, 61*(2), 120–140. https://doi.org/10.1111/jscm.12215
5. Cohen, J. (1960). A coefficient of agreement for nominal scales. *Educational and Psychological Measurement, 20*(1), 37–46. https://doi.org/10.1177/001316446002000104

6. Culot, G., Podrecca, M., & Nassimbeni, G. (2024). Artificial intelligence in supply chain management: A systematic literature review of empirical studies and research directions. *Computers in Industry, 162*, Article/ 104132. https://doi.org/10.1016/j.compind.2024.104132
7. Dwivedi, Y. K., Hughes, L., Baabdullah, A. M., Ribeiro-Navarrete, S., Giannakis, M., Al-Debei, M. M., & Wright, R. (2021). Artificial intelligence (AI): Multidisciplinary perspectives on emerging challenges, opportunities, and agenda for research, practice, and policy. *International Journal of Information Management, 57*, 101994. https://doi.org/10.1016/j.ijinfomgt.2019.08.002
8. Financial Times. (2025). AI agents: From co-pilot to autopilot. *Financial Times Tech Review*.
9. Fragiadakis, G., Diou, C., Kousiouris, G., & Nikolaidou, M. (2024). Evaluating human-AI collaboration: A review and methodological framework. *arXiv preprint arXiv:2402.01876*. https://arxiv.org/abs/2402.01876
10. Guest, G., Bunce, A., & Johnson, L. (2020). How many interviews are enough? An experiment with data saturation and variability. *Field Methods, 32*(1), 59–82. https://doi.org/10.1177/1525822X19863616
11. Haindl, M., Reisch, L., & Kuhn, D. (2022). Human-in-the-loop decision-making: Integrating feedback for effective AI collaboration. *Journal of Decision Systems, 31*(3), 310–328. https://doi.org/10.1080/12460125.2022.2071942
12. Haindl, P., Buchgeher, G., Khan, M., & Moser, B. (2022). Towards a reference software architecture for Human-AI teaming in smart manufacturing. *arXiv preprint arXiv:2209.09120*. https://arxiv.org/abs/2209.09120
13 .Hair, J. F., Black, W. C., Babin, B. J., Anderson, R. E., & Tatham, R. L. (2022). *Multivariate Data Analysis* (8th ed.). Cengage Learning.
14. Kushtia, H. J. (2023). The integration of artificial intelligence in supply chain management: A comprehensive review. *ORGANIZE: Journal of Economics, Management and Finance, 2*(3), 45–67.
15. Li, Z., Wang, Z., & Xu, X. (2022). Artificial intelligence for supply chain optimization: A review and future directions. *Computers & Industrial Engineering, 168*, 108028. https://doi.org/10.1016/j.cie.2022.108028
16. Makridakis, S. (2017). The forthcoming artificial intelligence (AI) revolution: Its impact on society and firms. *Futures, 90*, 46–60. https://doi.org/10.1016/j.futures.2017.03.006
17. Malakooti, B., & Raman, S. (2021). Artificial intelligence in operations and supply chain management: A review and bibliometric analysis. *Expert*

Systems with Applications, 176, 114890. https://doi.org/10.1016/j.eswa.2021.114890

18. MDPI. (2023). Intelligent supply chain management: A systematic literature review on artificial intelligence contributions. *Information, 14*(7), 356. https://doi.org/10.3390/info14070356
19. Meske, C., Bunde, E., Schneider, J., & Gersch, M. (2022). Explainable artificial intelligence: Objectives, stakeholders, and future research opportunities. *Information Systems Management, 39*(1), 53–63. https://doi.org/10.1080/10580530.2021.1894841
20. Michael, K., & Miller, K. W. (2020). The ethics of AI and robotics: A mapping of the issues. *Computers in Society, 37*(1), 1–21.
21. Nelson, J. P., Biddle, J. B., & Shapira, P. (2023). Applications and societal implications of artificial intelligence in manufacturing: A systematic review. *Journal of Manufacturing Systems, 66*, 81–95.
22. NVivo (2024). *NVivo qualitative data analysis software* (Version 14). QSR International.
23. Queiroz, M. M., Ivanov, D., Dolgui, A., & Wamba, S. F. (2020). Impacts of epidemic outbreaks on supply chains: Mapping a research agenda amid the COVID-19 pandemic through a structured literature review. *Annals of Operations Research, 297*(1–2), 635–682.
24. Revilla, E., Saenz, M. J., Seifert, R., & Ma, L. (2023). Human–artificial intelligence collaboration in prediction: A field experiment in the retail industry. *Journal of Management Information Systems, 40*(2), 295–323. https://digitalsc.mit.edu/wp-content/uploads/2024/02/Revilla-Saenz-Seifert-JMIS-2023_Human-Artificial-Intelligence-Collaboration-in-Prediction-A-Field-Experiment-in-the-Retail-Industry.pdf
25. Revilla, E., Saenz, M. J., Seifert, R., & Ma, Y. (2023). Human–AI collaboration in supply chains: From decision-support to supervisory control. *International Journal of Operations & Production Management, 43*(5), 678–701. https://doi.org/10.1108/IJOPM-05-2022-0312
26. Samuels, J., Smith, K., & Zhang, L. (2024). Examining the integration of artificial intelligence in supply chain management from Industry 4.0 to 6.0: A systematic literature review. *Frontiers in Artificial Intelligence, 7*, 1165. https://doi.org/10.3389/frai.2024.1165
27. Samuels, J., & Ortega, P. (2024). Artificial intelligence and supply chain resilience: Lessons from the COVID-19 pandemic. *International Journal of Production Research, 62*(4), 1012–1034. https://doi.org/10.1080/00207543.2023.2245678
28. Samuels, A. (2025). Examining the integration of artificial intelligence in supply chain management from Industry 4.0 to 6.0: A systematic

literature review. *Frontiers in Artificial Intelligence, 7*, Article/ 1477044. https://doi.org/10.3389/frai.2024.1477044

29. Schoenherr, T., & Speier-Pero, C. (2020). Data science, predictive analytics, and big data in supply chain management: Current state and future potential. *Journal of Business Logistics, 41*(2), 120–132. https://doi.org/10.1111/jbl.12235
30. Shahzadi, G., Jia, F., Chen, L., & John, A. (2024). AI adoption in supply chain management: A systematic literature review. *Journal of Manufacturing Technology Management, 35*(4), 611–632. https://doi.org/10.1108/JMTM-06-2023-0201
31. Siagian, I., Widjaja, A., & Prasetyo, Y. (2021). Leveraging artificial intelligence to build supply chain resilience during COVID-19. *Operations Research Perspectives, 8*, 100186. https://doi.org/10.1016/j.orp.2021.100186
32. Simon, A., Kumar, S., & Verma, R. (2025). Human-artificial intelligence collaboration in supply chain outcomes: The mediating role of responsible artificial intelligence. *Annals of Operations Research*. https://doi.org/10.1007/s10479-025-06592-1
33. Stanford HCAI. (2025). Human-centered AI. Stanford University Human-Centered AI Institute. Retrieved from https://hai.stanford.edu/
34. Te'eni, D., Yahav, I., Zagalsky, A., Schwartz, D. G., & Silverman, G. (2023). Reciprocal human-machine learning: A theory and an instantiation for the case of message classification. *Management Science, 69*(7), 3625–3645. https://doi.org/10.1287/mnsc.2022.4432
35. Vossing, F., Mühlroth, C., & Bican, P. (2022). Trusting artificial intelligence in organizations: A framework for research and practice. *Journal of Business Research, 141*, 593–606. https://doi.org/10.1016/j.jbusres.2022.05.019
36. Wamba, S. F., Gunasekaran, A., Dubey, R., & Ngai, E. W. T. (2018). Big data analytics and firm performance: Effects of dynamic capabilities. *Journal of Business Research, 70*, 356–365. https://doi.org/10.1016/j.jbusres.2016.08.009
37. Wamba, S. F., Queiroz, M. M., & Trinchera, L. (2021). Dynamics between artificial intelligence capabilities and supply chain resilience: A resource-based perspective. *International Journal of Production Economics, 235*, 108080. https://doi.org/10.1016/j.ijpe.2021.108080
38. Wang, G., Gunasekaran, A., Ngai, E. W. T., & Papadopoulos, T. (2021). Big data analytics in logistics and supply chain management: Certain investigations for research and applications. *International Journal of Production Economics, 231*, 107871. https://doi.org/10.1016/j.ijpe.2020.107871

39. Xu, X., Lu, Y., Vogel-Heuser, B., & Wang, L. (2021). Industry 4.0 and Industry 5.0—Inception, conception and perception. *Journal of Manufacturing Systems, 61*, 530–535. https://doi.org/10.1016/j.jmsy.2021.08.002
40. Yao, X., Lin, Y., & Ma, Y. (2022). A systematic review of AI in sustainable supply chain management. *Resources, Conservation and Recycling, 185*, 106457. https://doi.org/10.1016/j.resconrec. 2022. 106457
41. Zavolokina, L., Dolata, M., & Schwabe, G. (2020). FinTech transformation: How IT-enabled innovations shape the financial sector. *Electronic Markets, 30*(1), 1–9. https://doi.org/10.1007/s12525-019-00373-8
42. Zhang, J., Li, S., & Chang, K. (2024). Factors affecting human–AI collaboration performance in financial services. *Sustainability, 17*(10), 4335. https://doi.org/10.3390/su17104335
43. Zhang, Y., Ren, S., & Liu, Y. (2021). A bibliometric analysis of artificial intelligence research in operations management. *Technological Forecasting and Social Change, 165*, 120529. https://doi.org/10.1016/j.techfore.2020.120529
44. Zhao, K., & Liu, Y. (2021). Artificial intelligence for healthcare operations: Opportunities and challenges. *Production and Operations Management, 30*(4), 995–1010. https://doi.org/10.1111/poms.13323
45. Zhou, L., Chong, A. Y. L., & Ngai, E. W. T. (2022). Supply chain digitalization: A systematic literature review and future research directions. *International Journal of Production Economics, 236*, 108149. https://doi.org/10.1016/j.ijpe.2021.108149
46. Zhuang, C., Liu, J., & Xiong, H. (2021). Human-cyber-physical systems in Industry 5.0: A survey. *Journal of Industrial Information Integration, 26*, 100256. https://doi.org/10.1016/j.jii.2021.100256
47. Zomaya, A. Y., & Sakr, S. (Eds.). (2021). *Handbook of big data technologies*. Springer. https://doi.org/10.1007/978-3-030-20922-6
48. Zorina, Y. (2025). Intelligent Supply Chain Governance: Integrating AI for Sustainable, Resilient, and ESG Compliant Procurement. *Journal of Procurement and Supply Chain Management, 4*(2), 1–12. https://doi.org/10.58425/jpscm.v4i2.431
49. Zwass, V. (2021). Ethical AI for business: Opportunities and challenges. *Journal of Business Ethics, 173*(3), 543–556. https://doi.org/10.1007/s10551-020-05430-w

APPENDIX

Expert Interview Questions

1. Which supply chain or operations functions in your organization currently use AI, and how often are AI recommendations followed without changes?
2. What makes an AI recommendation trustworthy for you, and when do you still feel uncertain about its suggestions?
3. Are there situations where human approval is mandatory for AI decisions? How often do human overrides improve or hinder outcomes?
4. What data or system issues affect AI performance the most, and can you share an example of how an AI-related problem was addressed?
5. What training, guidance, or governance mechanisms exist to help humans collaborate effectively with AI, and how do you see these evolving in the future?

SURVEY QUESTIONS:

1. To what extent has your organization adopted AI in operations or supply chain management?
   A. Not at all
   B. Early experimentation
   C. Partial adoption in select areas
   D. Widespread adoption across functions
2. **Which supply chain functions currently use AI in your organization?** *(Select all that apply)*
   A. Demand forecasting
   B. Inventory management
   C. Logistics / transportation
   D. Procurement
   E. Supplier risk management
   F. Other (please specify)
3. How confident are you in AI-generated recommendations for operational decisions?
   A. Very low
   B. Low
   C. Neutral
   D. High
   E. Very high
4. What do you see as the greatest benefit of Human–AI collaboration?
   A. Cost savings
   B. Efficiency and speed
   C. Better decision quality
   D. Improved resilience / risk management

   E. Sustainability and compliance
5. What is the biggest barrier to effective Human–AI collaboration in your organization?
   A. Lack of trust in AI
   B. Data quality and availability issues
   C. High implementation costs
   D. Workforce resistance to change
   E. Lack of governance / ethical guidelines
6. How would you describe the balance of decision-making in your organization?
   A. Fully human-driven
   B. Mostly human, with some AI input
   C. Balanced (human + AI)
   D. Mostly AI-driven, with human oversight
   E. Fully automated (AI only)
7. To what extent do you agree that AI has improved decision quality in your organization?
   A. Strongly disagree B. Disagree
   C. Neutral D. Agree
   E. Strongly agree
8. How does your organization address ethical considerations in AI adoption?
   A. Formal governance framework in place
   B. Informal policies or discussions
   C. Ad-hoc / unclear approach
   D. No consideration of ethics currently
9. What level of training or support is provided to employees for Human–AI collaboration?
   A. None
   B. Minimal (basic awareness sessions)
   C. Moderate (role-specific training)
   D. High (structured programs and ongoing support)
10. How do you expect Human–AI collaboration to evolve in your organization over the next five years?
   A. No significant change
   B. Gradual improvements with limited adoption
   C. Moderate adoption across several areas
   D. Widespread adoption with significant transformation