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Beyond human-in-the-loop: Sensemaking between artificial intelligence and human intelligence collaboration

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ABSTRACT

In contemporary operational environments, decision-making is increasingly shaped by the interaction between intuitive, fast-acting System 1 processes and slow, analytical System 2 reasoning. Human intelligence (HI) navigates fluidly between these cognitive modes, enabling adaptive responses to both structured and ambiguous situations. In parallel, artificial intelligence (AI) has rapidly evolved to support tasks typically associated with System 2 reasoning, such as optimization, forecasting, and rule-based analysis, with speed and precision that in certain structured contexts can exceed human capabilities. To investigate how AI and HI collaborate in practice, we conducted 28 in-depth interviews across 9 leading firms recognized as benchmarks in AI adoption within operations and supply chain management (OSCM). These interviews targeted key HI agents, operations managers, data scientists, and algorithm engineers, and were situated within carefully selected, AI-rich scenarios. Using a sensemaking framework and cognitive mapping methodology, we explored how HI interpret and interact with AI across pre-development, deployment, and post-development phases. Our findings reveal that collaboration is a dynamic and co-constitutive process of institutional co-production, structured by epistemic asymmetry, symbolic accountability, and infrastructural interdependence. While AI contributes speed, scale, and pattern recognition in routine, structured environments, human actors provide ethical oversight, contextual judgment, and strategic interpretation, particularly vital in uncertain or ethically charged contexts. Moving beyond static models such as "human-in-the-loop" or "AI-assistance," this study offers a novel framework that conceptualizes AI and HI collaboration as a sociotechnical system. Theoretically, it bridges fragmented literatures in AI, cognitive science, and institutional theory. Practically, it offers actionable insights for designing collaborative infrastructures that are both ethically aligned and organizationally resilient. As AI ecosystems grow more complex and decentralized, our findings highlight the need for reflexive governance mechanisms to support adaptive, interpretable, and accountable human–machine decision-making.

1. Introduction

Artificial intelligence (AI), defined as the capacity of a machine to execute cognitive functions that are typically associated with human, underlying perceiving, reasoning, learning, and problem-solving capabilities, has now reached or even surpassed human performance in various domains, including games, standardized tests, and complex cognitive tasks requiring advanced thinking and strategic reasoning. For instance, AI systems are better than human-driven manual solutions in operations and supply chain management (OSCM) tasks, such as demand forecasting, inventory optimization, and route planning, areas that have long been considered highly complex and dependent on human expertise [27]. In particular, AI systems have demonstrated superior capabilities in real-time supply chain risk management by processing and analyzing massive volumes of logistical data to anticipate potential disruptions and inefficiencies before they escalate [1]. Moreover, AI enhances procurement processes and supplier selection by uncovering cost-saving opportunities and performance patterns that may escape human attention [130]. Transportation has also been revolutionized by AI: advanced AI-driven algorithms now optimize fleet scheduling, delivery operations, and load balancing with greater precision and efficiency than even the most seasoned logistics professionals [51]. These rapid advances have prompted some scholars to argue that even the most human-like traits, such as decision-making in uncertain supply chain environments, will eventually be replicable by machines. In short, AI is rapidly developing algorithms that "think humanly,"

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"think rationally," "act humanly," and "act rationally".

Given the astonishing progress of AI, Daniel Kahneman had questioned (and explored possible answers to) whether there are any inherent limitations to what AI can ultimately achieve, especially when provided with sufficient data. In his view, the distinction between tasks suited for humans and those better performed by machines is becoming increasingly irrelevant, and he advocates for the replacement of human decision-makers with algorithmic systems wherever it is feasible [80]. This perspective is echoed by Davenport and Kirby, who argue that computational systems already surpass the majority of humans in extracting meaningful insights from data, and that this disparity in analytical performance is expected to widen as AI technologies advance [38]. Along similar lines, Felin and Holweg [53] contend that AI is on track to outperform human reasoning and decision-making across a broad range of domains. Booyse and Scheepers [22] go further, suggesting that strategic functions such as supply chain network planning and even entire operational processes may soon be governed primarily by autonomous AI systems. Supporting this broader reconfiguration of intelligence, Hinton has asserted large language models are sentient and intelligent, and that "digital intelligence" will inevitably surpass human "biological intelligence", if it has not already done so [33,85].

Compared to machines, human intelligence (HI) are boundedly rational [118], processing information selectively and often relying on heuristics that introduce cognitive biases such as confirmation bias. These limitations hinder consistent, data-driven decision-making, particularly under complexity. In contrast, AI systems are engineered to efficiently handle vast volumes of structured data, applying statistical models or rule-based logic with speed, consistency, and minimal fatigue [119]. This divergence is encapsulated in Kahneman's dual-process theory,which distinguishes between two cognitive modes: System 1, fast, intuitive, and experience-driven, and System 2, slow, analytical, and deliberative [50]. While System 2 thinking is ideal for structured problems, System 1 often guides real-time decision-making in volatile, ambiguous environments where data may be incomplete or delayed. In OSCM, decisions frequently arise in contexts of disruption, such as political instability, raw material shortages, or unforeseen demand spikes [63]. In these cases, Type 1 decision-making, relying on intuition and experience, can be more effective than purely analytical approaches. For instance, an experienced supply chain professional may use "gut feel" to assess when to reorder inventory, even when quantitative data is scarce [109]. AI and cognitive technologies excel in well-defined tasks but struggle with open-ended problems requiring creative problem-solving, contextual understanding, and ethical judgment [65]. Unlike structured tasks with clear rules, real-world decisions involve uncertainty and incomplete information, where Type 1 processing, relying on experience and intuition, can outperform purely analytical reasoning [117]. Therefore, understanding how these two cognitive systems interact, and under what conditions they align or conflict, is essential to advancing effective decision-making in OSCM.

A new paradigm of collaboration is emerging, one that seeks to harness the distinct yet complementary strengths of AI and HI. AI offers unparalleled capabilities in processing large-scale data, automating routine tasks, and generating predictive insights with speed and precision. HI contributes strategic thinking, contextual judgment, ethical reasoning, and the ability to operate effectively under uncertainty. This evolving partnership aims not to replace one with the other, but to integrate both in a way that enhances decision-making quality, agility, and resilience, particularly in dynamic and complex environments where neither AI nor HI alone is sufficient [129]. Despite growing interest in AI across industries such as manufacturing, logistics, and technology etc. academic research has largely focused on AI as a standalone tool [12] and on HI within the fields of psychology and behavioral sciences [61]. There remains a significant gap in understanding how AI and HI interact and co-function in real-world, data-intensive operational contexts. This study addresses this gap by focusing on the OSCM domain, which is uniquely positioned at the intersection of technological sophistication and human decision-making complexity. OSCM is characterized by high data availability and widespread AI adoption, however it also involves frequent disruptions, ranging from geopolitical shifts to natural disasters, that require adaptive, experience-based human reasoning [18]. In such contexts, professionals like data analysts and operations managers serve as key HI agents, interpreting algorithmic outputs, applying domain expertise, and making context-sensitive decisions. This study poses the central research questions: *In the context of OSCM disruptions that require rapid, intuitive (System 1) responses alongside analytical, data-driven (System 2) processing, how do AI and HI agents interact, and what mechanisms enable their effective co-functioning in real-world operational environments?*

This study investigates the collaboration paradigm across key OSCM sectors, such as scheduling, logistics optimization, automated warehousing, demand forecasting, and robotics in manufacturing, as well as the role of external algorithm service providers, which some organizations rely on for AI solutions. These domains were chosen for their significant reliance on data, where AI technologies play a critical role in optimizing efficiency, improving decision-making, and addressing complex challenges; HI remains indispensable for managing uncertainty, making strategic decisions, and ensuring ethical considerations are upheld in dynamic and unpredictable environments [21,116]. The integration of both AI and HI is crucial to overcoming operational hurdles, ensuring human oversight in decision-making, and maintaining ethical standards. To understand the dynamics of this collaboration, the study employs a sensemaking approach, as defined by Weick and Weick [131], where decision-makers interpret and derive meaning from complex and ambiguous situations to guide their actions. In the context of AI-HI collaboration, sensemaking helps explain how professionals navigate the intersection of AI technologies and human judgment. This evolving interaction necessitates an exploration of the motivations, challenges, and decision-making processes that shape such collaborations. Through in-depth interviews with algorithm engineers, data scientists, and other professionals, the findings are translated into cognitive mapping, an analytical method that visualizes the relationships between key concepts and decision-making factors [47].

This research makes a significant theoretical contribution by bridging the fragmented understanding of AI and HI in the existing literature. Traditionally, AI and HI have been studied in isolation, with AI often viewed as a computational tool and HI as a decision-making mechanism. By examining the practical collaboration between these two forms of intelligence, this study reconstructs their relationship, demonstrating how they can work together synergistically to improve operational efficiency, adaptability, and ethical responsibility in real-world contexts. The theoretical contribution challenges the traditional distinction between AI and HI, offering a unified framework that emphasizes their complementary roles in addressing modern operational challenges. From a practical perspective, this research also offers valuable insights for businesses looking to optimize their operations by integrating AI and HI. More specifically, it outlines the processes through which these two intelligences collaborate, exploring the motivations and decision-making frameworks that guide their integration. By offering a structured understanding of how AI and HI can jointly contribute to operational strategies, this research provides actionable insights that can help organizations navigate the complexities of modern business environments, improve efficiency, and ensure ethical decision-making.

2. Literature review

2.1. Decision-making

Decision-making tasks involve choosing between actions, typically requiring committing to a particular course of action at a specific point in time, with consequences becoming apparent only later. A simple example might be deciding whether or not to pursue a PhD. A "good" decision might seem to be one leading to success, such as completing the PhD and securing a desirable academic position or succeeding in an alternative career. However, it is not straightforward. Since real-world scenarios are uncertain, good, and bad decisions must be judged on their theoretical merits, not solely on outcomes [123]. Recognizing uncertainty as inherent in decision-making contexts underscores the complexity involved. Uncertainty typically arises from limited or incalculable information about predicted outcomes [73]. Two main classifications of uncertainty have been identified: one based on sources (environmental or industry-specific) and another based on nature (exogenous network-related or endogenous firm-related) [74]. Given these differing perspectives on uncertainty, rationality through reasoning becomes central to understanding decision-making processes. Rationality posits individuals possess unlimited computational abilities, time, and knowledge, enabling decisions that maximize expected utility [29]. Economic models based on unbounded rationality, founded on homo economicus, emphasize maximizing expected utility and rely on statistical Bayesian models [104]. However, the assumption of unbounded rationality is unrealistic for human reasoning [34], yet frequently appears in management decision-making literature due to its economic implications. For instance, Bazerman and Moore [14] propose rational decision-making guidelines resembling unbounded rationality, emphasizing identifying relevant criteria and optimal information searches only until costs outweigh added value [11]. In contrast, the recognition of human cognitive limitations has led to the concept of bounded rationality, introduced by Herbert Simon [120]. Bounded rationality suggests decisions are based on satisficing criteria rather than optimizing, acknowledging limited computational power, time constraints, and imperfect information [34]. This realistic approach highlights heuristics or rules of thumb, leading to satisfactory but not necessarily optimal outcomes [75]. Kahneman and Tversky [81] demonstrated through prospect theory that real-world decisions deviate from unbounded rationality due to cognitive biases and heuristics. To manage these cognitive limitations and improve decision-making, individuals often employ rule-based thinking, developing rules through formal education, experiences, and social interactions [59]. These rules guide judgments, drive solutions, and determine action consequences [122]. This structured approach facilitates logical, sequential rule application, enabling evaluations of contexts, situations, and information using attribution and consequential reasoning to assess risk/reward payoffs [132]. Social psychologists find rule-based logic commonly employed in these scenarios [89]. A rule-based decision framework involves perception-comparison or interpretation-action processes. Perception gathers sensory information, significantly impacting subsequent interpretations and actions [39]. Factors such as prior knowledge and environmental context influence perception [68], with biases potentially causing systematic decision-making errors [83]. Interpretation involves comparing perceived information to stored memory [102], leading to action based on this comparison. Action efficiency depends on preceding stage accuracy and appropriateness of decision-making rules applied. This structured approach employs logic and causal inference rather than simple association to analyze situations and determine appropriate responses [28]. Thus, individuals can systematically frame decision problems, discern valuable information, and apply logical, sequential rules to make tailored, appropriate decisions [77].

2.2. Artificial intelligence involved

AI, according to the applications, can be classified or related into several sub-fields based on its applications: Artificial neural network and Rough set theory (‘thinking humanly’); machine learning (ML), expert system, and metaheuristics (‘acting humanly’); fuzzy logic (‘thinking rationally’); and agent-based simulation [99]. As AI continues to evolve into increasingly sophisticated applications, a closely related yet more specific concept has emerged, automated decision-making (ADM). ADM, though increasingly important, remains somewhat ambiguous despite being more specific than “artificial intelligence.” According to Araujo et al. [6], ADM is an oxymoron because decision-making inherently requires flexibility and contextual judgment, which automation excludes. The European Commission broadly defines ADM as software systems that autonomously or with human involvement make decisions related to social or physical systems based on data, impacting individuals or collectives [95]. Traditionally, decisions relied heavily on human competencies such as knowledge and experience [2]. However, ADM has advanced from descriptive analytics towards predictive and prescriptive capabilities, automating analysis and decisions even without human intervention [8]. These systems range from decision-support systems providing recommendations to fully autonomous systems independently adjusting operational strategies [62]. Despite these advancements, increased reliance on ADM introduces significant concerns about AI bias. AI bias occurs when the outputs of machine-learning models discriminate against specific groups or individuals, typically those historically marginalized based on gender, class, orientation, or race [96]. Although bias, as a deviation from a standard, does not inherently cause discrimination [54], understanding bias mechanisms is critical [5]. Bias contributing to discrimination includes historical [10], sampling [115], representation [84], measurement [52], evaluation [58], and algorithmic biases [76]. Addressing these biases requires ensuring AI explainability and transparency, interrelated challenges vital to maintaining fairness and trust. Explainability involves providing comprehensible explanations for AI decision-making processes, classified as ante-hoc model explainability [111] and post-hoc model explainability [121]. While various explainable models have been developed, explaining more complex systems like deep neural networks remains difficult, relying heavily on post-hoc explanations [23]. Evaluating explainability continues to pose challenges, as ambiguity remains regarding psychological perspectives [46], prompting researchers to employ qualitative human-participation metrics like interviews and questionnaires assessing satisfaction and trust. The intrinsic opacity of modern ML algorithms further complicates achieving transparency and explainability. Although examining algorithm construction and predictive variables is possible, comprehensively understanding algorithmic reasoning is inherently challenging [84]. Contemporary artificial neural networks recognize data patterns through iterative processes rather than logical reasoning [9]. While partial scientific explanations exist, algorithmic decisions remain fundamentally opaque due to unclear reasoning chains [42]. Finally, fairness and trustworthiness in AI, driven significantly by the explainability and transparency challenges mentioned above, are essential for ethical ADM. Ensuring fairness demands scrutiny of training data and algorithms to avoid perpetuating existing biases and inequalities [97]. Trustworthiness necessitates AI systems being reliable, transparent, and ethically aligned [126]. Opacity undermines trust, as developers themselves often cannot fully explain AI decision-making processes [31]. This "black box" phenomenon hinders diagnosing and correcting biases or errors, potentially producing arbitrary or unjustified decisions [35].

2.3. Human intelligence involved

Fast-and-slow dual-processing decision-making proposes two distinct types of information processing: Type 1 and Type 2, operating simultaneously but potentially leading to different conclusions from the same information [50]. For instance, in supply chain management, Type 1 processes might quickly trigger an impulse to reorder inventory immediately upon noticing sudden demand spikes or supplier disruptions. Conversely, Type 2 processes thoughtfully analyze historical sales data, lead times, inventory costs, supplier reliability, and long-term forecasts before decisions. Initially described distinctly, Type 1 was quick, automatic, and intuitive, and Type 2 slower, deliberate, and controlled [57]. However, these descriptions proved insufficient, as not all slow processes are serial and controlled, nor are all quick processes automatic and inflexible [113]. Thus, processes are now classified as two types rather than two distinct systems. Type 1 processes are autonomous, automatically triggered by specific stimuli without high-level control input [79]. Type 2 processes can decouple hypothetical reasoning from real-world representations, operating abstractly and deliberately, requiring significant cognitive effort and analytical precision [44]. The effectiveness of Type 1 lies in swiftly producing decisions in urgent scenarios, but this rapidity often sacrifices analytical precision typical of Type 2. The reliance on rapid intuitive processing, as seen in Type 1, can lead directly to heuristic biases. Closely related to intuitive decision-making, heuristics bias involves reliance on initial information, anchoring subsequent judgments towards it [88]. Anchoring bias in group decision-making compounds, disproportionately influencing consensus through dominant initial opinions, irrespective of validity [43]. In operational contexts, anchoring can amplify the 'bullwhip effect', where minor demand variations escalate across supply chains. Group dynamics further magnify biases through mechanisms like groupthink, driven by overoptimism and ingroup favoritism [101]. Structured group strategies, such as using 'devil's advocates' [82], 'Delphi and focus groups' [17], and 'nominal group techniques' [125], reduce groupthink by fostering critical reflection and debate. Such collaborative deliberation utilizes collective cognitive capacities, known as 'collaborative cognition', effectively identifying and mitigating biases through reflective thinking [37]. Nonetheless, collaboration alone cannot fully prevent anchoring bias, especially in ambiguous situations without definitive answers [98]. Given these inherent limitations in analytical and collaborative approaches, intuitive decision-making becomes particularly beneficial in unprecedented or highly ambiguous scenarios [70]. Cognitive technologies, proficient in probabilistic analyses, struggle with novel problems demanding creative thinking [107]. Unlike controlled board games, real-world decision-making is inherently messy, rendering analytical methods insufficient [40]. Thus, decision-makers often leverage intuition based on tacit experience and personal judgment, even if their reasoning remains difficult to articulate, described as "just feels right" [3] or "gut feel" [109].

2.4. Collaborative paradigm

Based on different levels of human involvement, collaboration with AI-based systems can be classified into three types [26]: Human-only approach (refers to Human involved): No AI is involved; all decisions are made solely by humans. Human-out-of-the-loop (refers to AI involved): AI autonomously makes and implements decisions without human intervention or the possibility of override. Collaboration: This approach allows the supervisor to oversee the entire activity of the AI system, including its broader economic, societal, legal, and ethical impacts [134]. It ensures that the human can override any decisions made by the AI system. The continuum of rational behavior illustrates that top-down and bottom-up applications contribute differently to AI capabilities. Top-down applications use logical rules and structured knowledge representation to improve tasks like perception and interpretation, enabling machines to mimic human-like thinking processes [24]. These are effective in contexts requiring structured and logical processing. In contrast, bottom-up applications rely on AI, particularly ML, to manage complex actions requiring higher intelligence. Instead of following predefined rules, these systems learn from data, improving through experience [128]. As modern systems increasingly integrate both approaches, decision-making benefits from combining the efficiency of machines with human oversight, a concept referred to as "having a human in the loop" [124]. Human-in-the-loop (HITL) settings involve automated processes requiring human interaction, integrating human knowledge and experience into systems like ML models [100]. This interactive ML approach is defined by Holzinger et al. [72] as algorithms that can interact with agents, including humans, and optimize their learning behavior. It encourages ML development through direct human interaction with the learning system [60]. HITL moves beyond data preprocessing by involving humans in the actual learning phase [114]. Unlike traditional HITL, Human-over-the-loop (HOTL) shifts humans to a supervisory role, allowing AI to handle routine tasks while reserving human input for complex decisions [56]. In this model, humans monitor and intervene only when AI encounters ambiguous or unforeseen scenarios [78]. In high-stakes domains like autonomous driving, HOTL enhances safety and reliability through timely human intervention [90]. In more rigorous oversight settings, Human-in-command (HIC) systems emphasize human authority in the operation of AI, ensuring decisions remain under human control [41]. This guarantees ethical and legal compliance by placing humans at the core of decision-making [49]. HIC is vital in areas involving ethical risks, reinforcing accountability and moral responsibility [110]. Human oversight also brings flexibility and contextual awareness, capturing emotional and cultural differences that AI may overlook [66]. This aligns with Chin et al. [32], who emphasize the importance of reflexive and context-sensitive oversight to ensure responsible and inclusive technological governance. Conclusively, integrating HI and AI leverages the strengths of both: AI contributes speed, scale, and pattern recognition, while humans provide ethical judgment, creativity, and contextual sensitivity. Their collaboration enhances decision quality, improves adaptability in complex environments, and ensures that automated systems remain aligned with human values.

3. Methods

Sensemaking, an active and iterative process by which decision-makers interpret ambiguous cues, assign meaning, and adjust their actions accordingly [131], provides the theoretical foundation for this study. Guided by this framework, we adopt a qualitative, exploratory approach, using multiple case studies to investigate collaborative interactions between AI and HI in OSCM contexts. Case studies are particularly effective for capturing the complexity of real-world phenomena, enabling deep exploration of "how" questions within their natural settings [133]. Specifically, we selected scenarios within each case characterized by close and ongoing interaction between human decision-makers and AI systems. This targeted selection allows detailed examination of critical sensemaking elements, such as trust, interpretability, iterative feedback, and adaptive decision processes, revealing how humans integrate experiential knowledge, intuition, and contextual reasoning with AI-generated insights. Ultimately, this method supports robust theory-building, illuminating the dynamics through which AI and HI collaboratively construct meaning and strengthen decision-making resilience [16].

3.1. Case and scenario selection

As shown in Fig. 1, the case selection begins with the *Innovators*, organizations that are actively integrating AI technologies into their operational processes. The Innovators are divided into two categories: *Transportation Innovators* and *Retail Innovators*. Transportation Innovators (Cases A, B, C) were selected due to the complexity and data-intensive nature of the transportation sector, where AI is applied to optimize logistics networks, route planning, and predictive maintenance. The sector's reliance on real-time data for decision-making provides a relevant context for examining AI's role in improving operational efficiency and decision quality. Retail Innovators (Cases D, E), on the other hand, were chosen for their focus on customer experience and demand forecasting. In retail, AI is used to analyze large volumes of transactional data, personalize marketing, and optimize inventory levels, which makes it an ideal sector for studying how AI aids decision-making in dynamic, customer-driven environments. Alongside the Innovators, the study includes *Solution Providers*, firms that play a key role in enabling the adoption and integration of AI in operations and supply chains. These include custom AI service providers (Cases F, G, H) that develop tailored AI solutions to address specific operational challenges, and AI fine-tuning consultants (Case I) that help businesses optimize the

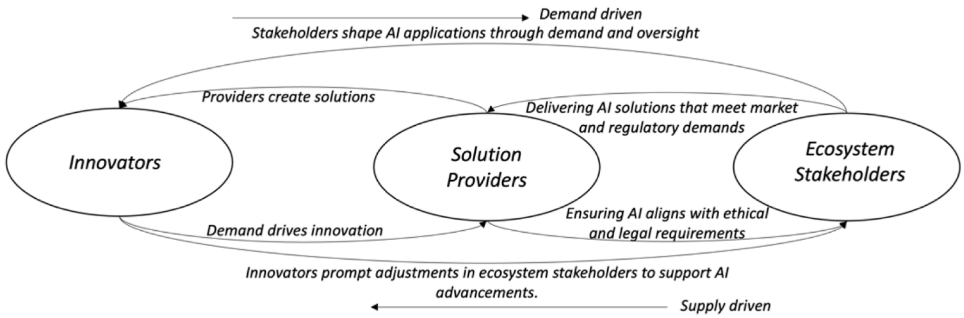

Fig. 1. Case studies onion model (Source: The Authors).

performance of AI systems after deployment. These Solution Providers were included to offer insights into the development, customization, and continuous refinement of AI technologies, which are essential for understanding how AI systems are implemented and adjusted to fit real-world operational needs. Finally, the outer layer of the framework consists of *Ecosystem Stakeholders*, such as regulators and industry associations. These actors influence the environment in which AI operates, helping to shape the ethical, legal, and operational standards that govern AI applications. Regulators establish the frameworks within which AI systems must operate, ensuring compliance and building trust, while industry associations facilitate collaboration, knowledge-sharing, and the setting of best practices.

Each scenario represents a specific decision-making function where AI systems are embedded into core business processes and require human involvement to interpret, adjust, or act upon algorithmic outputs (Table 1). In Case A (Airline supply chain), the scenario of scheduling and planning captures a common AI application where optimization models generate flight and crew schedules, and human planners adapt these in response to real-time constraints like weather or airport delays. Case B (End-to-end logistics) focuses on logistics and route optimization, a representative scenario where AI identifies efficient delivery routes, while human operators assess feasibility and make final adjustments based on customer needs and operational constraints. In Case C (Agri-food supply chain), two scenarios, automated warehousing and risk management of logistics, illustrate how AI handles inventory and disruption detection, while humans ensure continuity and manage exceptions, especially in perishable goods handling. Case D (E-commerce) centers on demand forecasting, where AI models detect purchasing patterns and predict sales, but human engineers refine outputs by integrating promotional schedules and external signals. Case E (Digital pharmaceutical supply chain) involves recommendation and decision support, where AI assists in planning and compliance tasks, and human decision-makers ensure that regulatory and safety standards are upheld. Case F (Robotics and manufacturing) demonstrates how human experts supervise and refine AI-driven automation on production lines, representing the industrial integration of AI. Case G (Algorithm solution services) and Case H (Intelligent decision-making services) offer a broader view into how AI is customized and iteratively improved through human input, covering cross-sectoral deployment of AI for operational enhancement. Finally, Case I (Supply chain transformation

Table 1
Overview of the cases and scenarios (Source: The Authors).

ID-Country-Year Founded	Industry	Scenarios	Code for Discussion	Interviewees	Year of Experience
A-US-1924	Airline supply chain	Scheduling and planning	R1	Operations Research Scientist	1-5
			R2	Operations Research Scientist	1-5
			R3	Decision Science and Analytics Leader	1-5
B-Denmark-1976	End-to-end logistics	Logistics and route optimization	R4	Operations Research Scientist	1-5
			R5	Operations Research Scientist	1-5
			R6	Solution Design Engineer	1-5
C-UK-2000	Agri-food supply chain	Automated Warehousing	R7	Director of Planning and Analytics	6-10
			R8	Senior Data Scientist	1-5
		Risk management of logistics	R9	Data Scientist Team Lead	6-10
D-China-1998	E-commerce	Demand forecasting	R10	Algorithm Engineer	1-5
			R11	Algorithm Engineer	1-5
			R12	Algorithm Engineer	1-5
			R13	Algorithm Engineer	1-5
			R14	Senior Algorithm Engineer	1-5
E-Netherlands-2006	Digital pharmaceutical supply chain	Inventory optimization	R15	Integration Leader	1-5
		Recommendation and decision support	R16	Head of Architecture	1-5
F-UK-1997	Robotics and automation manufacturing	Robotics and manufacturing	R17	Director	10-15
G-US-2000	Algorithm solution services	AI-enhanced operational optimization services	R18	Operations Research Scientist	1-5
			R19	Operations Research Scientist	1-5
H-China-2016	Intelligent decision-making services		R20	Vice President	6-10
			R21	Senior Algorithm Engineer	6-10
			R22	Vice President	6-10
			R23	Data Scientist	6-10
			R24	Senior Algorithm Engineer	1-5
			R25	Senior Algorithm Engineer	6-10
I-UK-1845	Supply chain transformation services	Ethical AI integration services	R26	AI service Manger	6-10
			R27	Senior AI consultant	1-5
			R28	AI Lead	6-10

services) focuses on ethical AI integration, where human consultants ensure that AI applications align with legal, ethical, and organizational standards. Together, these scenarios span a range of industries, from transportation and retail to manufacturing and consulting, and capture varying degrees of AI maturity and human involvement. Their selection provides a strong foundation for analyzing how humans and AI co-produce decisions, offering both breadth and depth for understanding collaboration mechanisms in operational practice.

3.2. Data collection

Data collection for this study occurred between September 2022 and August 2023, with the final cognitive mapping and synthesis completed in mid-2024. To comprehensively understand the dynamics of collaboration, this research strategically selected benchmark cases that demonstrated advanced expertise and maturity in applying such collaboration within OSCM contexts. These cases were chosen for their potential to provide information-rich, practice-oriented insights. Accordingly, we included interviewees across a broad spectrum of organizational roles, ensuring that both technical implementation and strategic decision-making perspectives were captured. The 28 experts interviewed were carefully selected from seven industries, airline, logistics, agri-food, e-commerce, pharmaceutical supply chains, manufacturing, and AI solution services, representing a mix of technical, managerial, and strategic perspectives. The diversity of roles ensures a comprehensive view of AI-HI collaboration. For instance, Operations Research Scientists and Algorithm Engineers are pivotal to understanding the technical implementation and optimization of AI systems. These professionals are deeply involved in designing and refining AI algorithms, ensuring that AI decisions are data-driven and optimized for efficiency. They are integral to the decision-making process as they shape the AI systems that human decision-makers interact with, making their insights invaluable for understanding the intersection of human and AI-driven logic. Alongside them, Data Scientists are crucial because they translate large datasets into actionable insights, offering a bridge between raw data and decision-making applications. They ensure that AI models remain relevant to real-world scenarios by processing and interpreting complex data sets that inform decisions, thus acting as key agents in the AI-HI interaction. Meanwhile, Integration Leaders and Solution Design Engineers provide strategic oversight in implementing AI technologies into existing systems, ensuring that the AI models are not just theoretical but practically applicable within operational workflows. Their expertise ensures that AI is integrated in a way that aligns with the broader organizational goals and processes, making them essential for understanding the structural aspects of AI deployment. Further complementing these technical roles, Senior Managers, Vice Presidents, and Directors play an essential role in framing AI's contribution within larger organizational strategies. While their direct involvement with AI implementation might be less technical, their strategic oversight and decision-making responsibilities provide key insights into how AI is positioned in the broader business context. They evaluate how AI can enhance or disrupt existing decision-making processes and provide leadership to align AI initiatives with organizational goals. These senior leaders, alongside Consultants, who offer external expertise, offer a broader view of the business implications of AI-HI collaboration, focusing on aligning AI solutions with market trends, regulatory considerations, and industry standards. The combination of these roles in the sample reflects a balanced representation of both the technical and strategic sides of AI implementation in decision-making.

3.3. Data analysis

Cognitive mapping is a structured, qualitative method that visually captures how individuals understand and reason through complex decision-making contexts. Following Kosko [86], a cognitive map consists of nodes (representing decisions, concepts, or influencing factors) connected by arrows indicating causal or dependency relationships. These maps allow the articulation of how participants perceive and prioritize different elements within a system [55]. The typical structure of a cognitive map follows a hierarchical logic [48], with actions and options at the bottom, strategic decisions and enabling processes in the middle, and ultimate goals or organizational objectives at the top. To systematically explore the integration of AI and HI in decision-making, this research conducted a series of semi-structured interviews with industry professionals. Each interview was structured around three key stages of the AI-HI implementation lifecycle [13,64]: *Pre-development:* (1) Early development, (2) Piloting, *Deployment:* (3) Implementation, *Post-development:* (4) Acceptance of deliverables, and (5) Future application. These stages were designed to reflect the temporal and strategic flow of AI-HI integration from initial consideration to future expansion (see Table 2, Appendix A for the full set of interview questions).

During each interview, participants engaged in real-time cognitive mapping using Miro, a collaborative digital whiteboard. Each participant began by constructing a map reflecting their organization's decision-making logic. Crucially, maps from earlier sessions were iteratively presented to subsequent participants, who were encouraged to comment on, revise, or expand upon existing structures. This accumulative method enabled a form of distributed sense-making, allowing perspectives to converge, diverge, or evolve over time. At the end of each session, maps were saved with metadata and layered into a version-controlled master map. After all interviews were completed, participants reviewed and validated the final composite map to ensure accuracy and ownership of the data. A three-stage synthesis process was then conducted. First, key nodes were identified and coded into six categories: decision points, resources and capabilities, risks, enablers, organizational structures, and external drivers. Second, relational edges were standardized by direction, polarity (positive/negative influence), and strength (weak/moderate/strong). Third, the data were processed using NVivo 14 to generate adjacency matrices and visual network graphs. These revealed shared structural patterns, critical decision junctures, and points of organizational friction across firms. Finally, a composite HI–AI cognitive map was created by integrating the validated human maps with system-level documentation from AI architectures. This synthesis captured how human and artificial agents coordinate, override, or defer to each other within decision-making workflows. The resulting visualization (see Fig. 2) illustrates the dynamic interplay of trust calibration, collaborative logic, and intervention thresholds that govern AI-HI interaction throughout the decision lifecycle.

4. Results

4.1. AI involved

The AI decision-making process in both transportation and retail innovators hinges on the systematic collection, integration, and analysis of extensive and varied datasets, which are essential for ensuring that the models used for predictions and decisions are reliable, robust, and scalable (Fig. 3 shows the overall cognitive map for innovators, with detailed case maps in Appendix B). The pre-development stage is foundational in this process, where data from diverse sources is gathered, cleaned, and structured to ensure consistency. In the transportation industry, data from a range of sources, such as flight schedules, traffic management systems, IoT sensors, and weather forecasts, is meticulously collected and standardized. This structured data is crucial for ensuring the AI systems can operate smoothly, as unstructured data or inconsistencies could lead to significant operational inefficiencies. Similarly, in retail, vast amounts of data are collected, including historical sales data, customer interactions, market trends, and even external factors like weather and economic indicators. This comprehensive data collection forms the backbone for predictive modeling, where the AI models are empowered to analyze large, diverse datasets to derive actionable insights. The process of integrating these datasets,

Table 2
Interview structure overview (Source: The Author).

Stages	Section	Focus	Purpose
Pre-development	Background	Interviewee and Company	Understand participants ‘human intelligence’ role and the organizational AI scenario setting
		AI-HI Collaboration Drivers	Explore factors (e.g., market trends, technology, organizational culture) driving AI-HI collaboration.
	Early development	Evaluation of AI and HI Applications	Investigate how AI and HI collaboration is evaluated and integrated into early-stage decision-making.
		Scenario Selection and Model Decision	Understand how AI and HI decision-making functions are selected and alternative approaches considered.
		Key Success Factors	Identify factors that make AI-HI collaboration successful in early development.
	Piloting	Pilot Experiments and Simulations	Assess experiments/simulations to test AI-HI collaboration, unintended outcomes, and blind spots.
		Evaluation of Initial Results	Understand how test results inform AI-HI integration adjustments.
Deployment	Implementation	Managing AI-HI Decision-making	Explore how AI and HI are integrated into real-world decision-making, including stakeholder involvement.
		Handling Organizational and Environmental Factors	Assess how external factors influence AI-HI implementation.
		Failure Management	Understand how implementation setbacks are managed and lessons applied.
Post-development	Acceptance of deliverables	Performance and Accountability	Evaluate AI-HI decision-making effectiveness with performance metrics and accountability mechanisms.
		Improving Future Projects	Explore strategies to improve AI-HI decision-making in future projects.
	Future application	Expansion to Tactical and Strategic Decision-making Levels	Investigate plans to expand AI-HI collaboration into strategic decision-making levels.

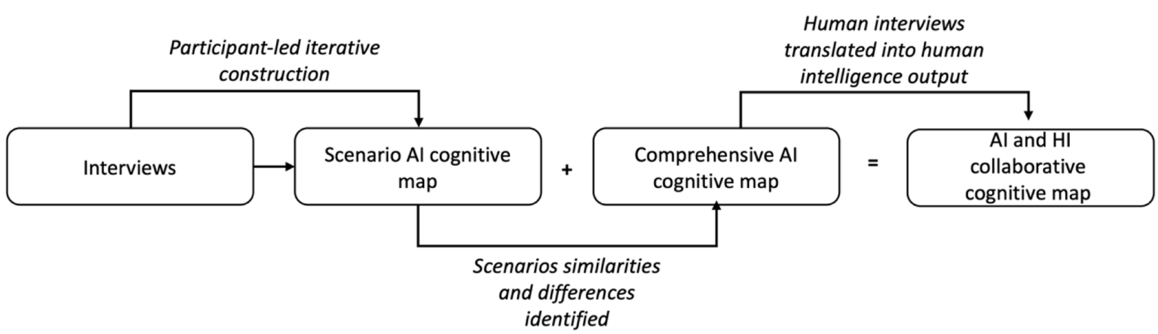

Fig. 2. Data analysis process (Source: The Authors).

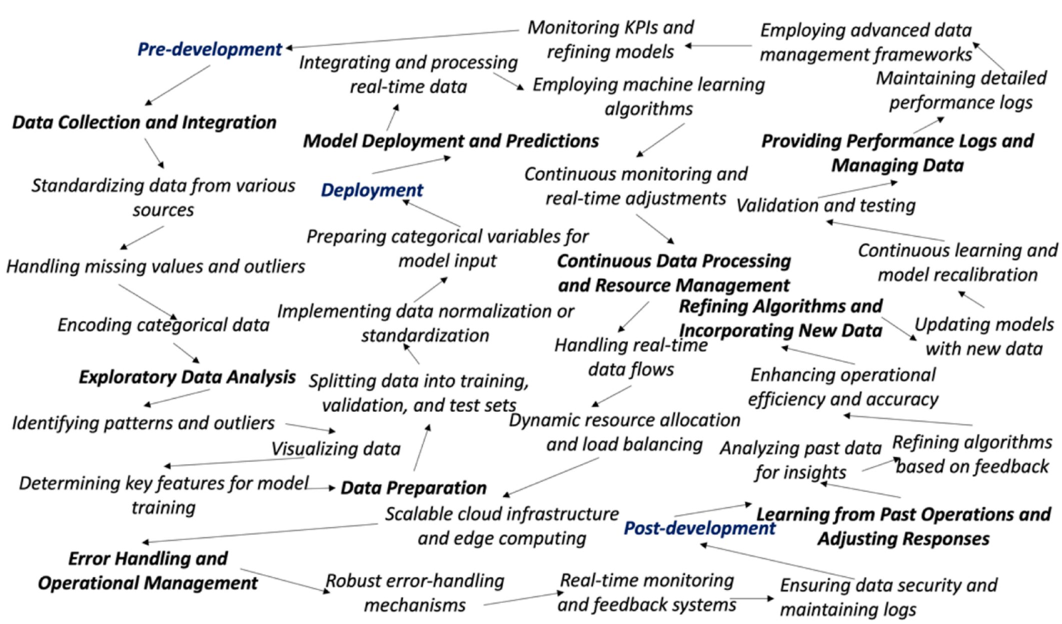

Fig. 3. AI decision making process (Source: The Authors).

while ensuring that they are clean and consistent, is crucial for predictive accuracy.

Following the data collection, the Exploratory Data Analysis (EDA) stage serves as a critical step in both transportation and retail sectors. EDA involves using analytical techniques to uncover patterns, relationships, and trends in the raw data. In transportation, EDA is employed to identify significant relationships, such as how weather conditions may influence flight delays or how traffic congestion impacts delivery times. This phase often uses advanced data visualization techniques, such as scatter plots, heatmaps, and time-series analysis, to detect underlying trends and correlations. Similarly, in retail, EDA helps to identify demand patterns, seasonal variations, and the influence of external factors, such as promotions or weather, on consumer behavior. Retailers might use clustering techniques to segment customers based on purchasing patterns or geographic location, which helps to tailor marketing efforts and optimize stock levels accordingly. In both industries, EDA helps pinpoint significant features for model training, ensuring that the data fed into AI models is both meaningful and predictive. By identifying and handling outliers, EDA improves the dataset's integrity and ensures that AI systems can deliver accurate predictions.

Once data has been processed and analyzed, the next step is data preparation, which is a meticulous and critical phase in developing ML models. Raw data must be refined to ensure it is compatible with ML algorithms, and this involves steps like normalization and standardization. Normalization scales data to a consistent range, usually between 0 and 1, which is crucial for models that are sensitive to data scale, such as neural networks or support vector machines. Standardization, on the other hand, adjusts data to have a mean of zero and a standard deviation of one, which is especially useful for models that assume Gaussian distribution. In both the transportation and retail industries, categorical variables, such as flight types or customer preferences, are converted into numerical formats using techniques like one-hot encoding or label encoding. This transformation is essential, as most ML models can only process numerical data. Furthermore, the dataset is split into training, validation, and test sets. This splitting ensures that the model can be trained on one subset, tuned on another to avoid overfitting, and evaluated on a separate test set to measure its performance. The rigor of this preparation process plays a crucial role in determining how well AI models can generalize to new, unseen data, a key factor in their reliability and predictive power.

The deployment stage represents the integration of AI models into real-world operational systems, marking the transition from theory to practice. Here, AI models process continuous data streams to make real-time adjustments and predictions. In transportation, for example, AI models dynamically adjust flight schedules based on incoming weather updates, crew availability, and flight status reports, optimizing flight routes to avoid delays or reallocate resources efficiently. Similarly, in retail, AI models process real-time sales data and customer interactions to adjust inventory levels, predict demand fluctuations, and offer personalized product recommendations. To ensure these models can handle the immense computational load required for real-time processing, both sectors rely heavily on cloud computing and edge processing technologies. These infrastructures enable the AI systems to scale and handle large volumes of data without compromising on response time. Cloud platforms also offer the advantage of centralized data storage and processing power, ensuring that operational decisions can be based on the most up-to-date information. Additionally, real-time monitoring systems are employed to track the performance of AI models and ensure they are working optimally, especially during peak operational periods, such as holiday seasons in retail or during weather disruptions in transportation.

The post-development stage is essential for continuous improvement and adaptation of AI systems based on new data and operational insights. This stage focuses on refining AI models by integrating past performance data, user feedback, and real-time inputs. In transportation, historical data on flight delays, maintenance issues, and crew performance is analyzed to optimize flight scheduling and route planning further. The AI system adapts to new insights, for example, by adjusting algorithms to accommodate recurring flight delays due to specific weather conditions or mechanical failures. In retail, the post-development stage focuses on fine-tuning demand forecasts, inventory management strategies, and recommendation systems by incorporating new data on sales, customer feedback, and changing market conditions. This phase also involves real-time recalibration of models to ensure that they remain responsive to evolving business needs and consumer behaviors. AI models in both sectors benefit from continuous learning processes, where algorithms are updated as new patterns and outliers are identified, improving their predictive accuracy and operational relevance. Error handling mechanisms and performance logs are integral to this stage, ensuring that any operational anomalies are captured and addressed. Moreover, this phase allows organizations to identify and fix issues in the models, providing an opportunity to make system-wide improvements and further align AI-driven decisions with evolving business strategies and market demands.

4.2. HI involved

In flight scheduling and crew management (Case A), the role of human involvement remains indispensable despite significant AI advancements. As highlighted by interviewee R1, "Aviation scheduling is inherently complex and requires more than algorithmic precision; it demands an understanding of human experiences and the ability to adapt in real-time." This insight stresses the importance of human expertise in making informed decisions about which algorithms to employ, especially when the nature of scheduling involves details such as crew preferences, fatigue levels, and interpersonal dynamics. AI systems, as R2 and R3 note, often struggle with these human elements. R2 emphasizes that "AI systems often cannot fully grasp the personal aspects that affect crew management, such as individual preferences and team dynamics." The dynamic nature of the aviation industry, influenced by ever-changing regulations and customer needs, demands flexibility that AI alone cannot provide. Human planners are crucial in adapting scheduling systems to meet new operational challenges. Furthermore, as R1 points out, human involvement is essential in error detection and resolution, particularly in cases where AI identifies patterns or anomalies but cannot understand their context. Finally, continuous human oversight ensures that the data fed into the system is accurate and up to date, which is vital for maintaining the performance of AI-driven scheduling systems.

In logistics and route optimization (Case B), both HI and AI are necessary to address the complexities of real-time decision-making. R4 asserts, "Logistics management is not just about crunching numbers; it requires understanding and responding to human needs," which highlights the limits of AI in managing human-centric challenges, such as weather disruptions or road closures. AI can analyze fixed factors like route conditions, vehicle capacity, and traffic patterns, but human oversight is necessary to incorporate safety, delivery quality, and environmental impact considerations into route planning. As R5 notes, "Coordinators must weigh driver safety, delivery quality, and environmental impact alongside optimizing time and cost," underscoring that AI alone cannot handle the multifaceted nature of logistics management. Human involvement is particularly critical when disruptions occur, as emphasized by R6: "A responsive system that can quickly adapt to changing conditions and reroute resources is essential." This highlights the need for human intervention to manage unexpected events such as accidents or mechanical failures. Moreover, human experts are vital for optimizing last-mile delivery and ensuring that environmental and efficiency goals, such as reducing carbon emissions, are met. They make real-time adjustments based on the operational realities that AI alone may overlook. Ultimately, human oversight ensures that the AI-driven logistics systems remain adaptable and responsive, maintaining the overall efficiency and safety of the operations.

Automated warehousing (Case C) also demonstrates the critical role of human expertise in enhancing AI-driven processes. R7 emphasizes, “While AI can handle repetitive tasks with speed and precision, it lacks the ability to establish performance metrics and evaluate the broader implications of its decisions.” This reflects the limitations of AI in setting the standards by which its performance is measured and adjusting those standards over time based on evolving business goals. R8 further highlights that, “Developing accurate predictive models involves not just historical data but also an understanding of market trends and consumer behavior, areas where human insight is indispensable.” While AI excels at processing large datasets, it struggles with contextual differences that human experts can incorporate into predictive models, ensuring these models remain robust in dynamic environments. Continuous monitoring by humans is also crucial, as R9 points out, “AI systems can make errors or overlook context-specific details, which human operators can identify and correct.” This constant human oversight ensures that AI-driven warehousing systems are constantly improving and functioning efficiently. Furthermore, R9 highlights the importance of human involvement in pre-deployment tests to identify potential issues and refine the system, preventing costly errors when fully scaled.

In risk management within logistics (Case C), human involvement is essential for contextualizing AI-generated insights and ensuring that risk models are robust and adaptable to unforeseen circumstances. R8 stresses that “Developing accurate risk models requires historical data and also an understanding of real-world logistics operations and potential unforeseen variables,” which demonstrates that AI alone cannot address the complexities of logistics risk management. Human expertise is necessary to factor in these real-world contexts, ensuring that AI models can adapt to the dynamic nature of logistics operations. R9 adds, “AI systems can produce opaque outputs that are difficult to understand and trust without human interpretation.” This highlights the need for human professionals to interpret AI outputs in a way that is understandable and actionable. Additionally, R9 points out that humans play a crucial role in ongoing surveillance of AI systems, ensuring any anomalies or errors are promptly addressed. This constant human engagement helps maintain the integrity of AI-driven decision-making in logistics. Finally, R7 concludes, “AI can analyze vast amounts of data and identify risks, but it lacks the contextual understanding and ethical considerations that experienced human professionals possess,” reinforcing the critical importance of human professionals in ensuring AI decisions are ethical and contextually sound.

In demand forecasting and inventory optimization (Case D, E), human oversight is critical in managing the complexities and dynamic nature of retail and pharmacy operations. R10 explains, “Retail demand forecasting must adapt to numerous external factors such as economic changes, seasonal trends, and unforeseen events like pandemics,” which AI alone struggles to predict. R11 further emphasizes that during unpredictable events such as a pandemic, human expertise is necessary to adjust pricing and inventory strategies in real time. R12 highlights that operational tasks like managing courier services also demand human judgment, especially in the face of unforeseen disruptions such as traffic delays or vehicle breakdowns. As R13 and R14 note, human intervention is essential in refining AI models, especially when issues arise with demand prediction accuracy. R15–R16 stress that while AI can optimize stock levels, human expertise ensures compliance with industry regulations, patient safety in pharmacies, and swift responses to changes in demand that AI may miss. Furthermore, human involvement in training employees on new systems, such as ERP and Warehouse Management Systems (WMS), ensures smooth transitions and better adoption, as R16 explains, “employee training on new ERP and WMS systems is essential.”

In Case F, human expertise plays a pivotal role in supervising AI-driven robotics, ensuring these systems operate within safe and efficient boundaries while adapting to dynamic manufacturing conditions. As R17 emphasized, “Human expertise, judgment, and domain knowledge are invaluable for guiding and supervising AI-driven robotics,” underscoring the necessity of human-in-the-loop design. While AI systems are adept at repetitive optimization tasks, they fall short in handling real-time problem-solving, adjusting production lines, or responding to unexpected disruptions, areas where human adaptability is irreplaceable. R17 further highlighted, “Human involvement is critical for tasks that require adaptability and real-time problem-solving, areas where AI might struggle.” Beyond day-to-day operations, human operators contribute essential feedback to refine AI algorithms, identify subtle errors, and initiate continuous process innovation. Their involvement ensures minimal downtime and safeguards productivity. Moreover, humans serve as ethical gatekeepers, making decisions that AI, limited by algorithmic logic, cannot fully grasp, particularly in maintaining worker safety and aligning production with broader societal norms. Importantly, strategic foresight and long-term planning remain uniquely human strengths. While AI optimizes within defined parameters, human leaders in Case F interpret industry trends, anticipate disruptions, and shape innovation trajectories, keeping manufacturing agile and future ready.

In Cases G and H, human involvement in AI-enhanced operational optimization services ensures that technological systems remain strategically aligned with organizational objectives. R18 stressed that “Human oversight is necessary to ensure AI decisions are aligned with organizational objectives and strategic goals,” highlighting that AI-generated outputs must be interpreted through the lens of business relevance. As R19 added, “AI systems can optimize operations, but they need human supervision to ensure the outputs are practical and beneficial for the company’s specific context.” Human experts act as translators, integrating AI insights into broader business strategies (R20) and customizing solutions to reflect client-specific needs (R21). Furthermore, support and training provided by human consultants (R22) are integral to the effective implementation of AI tools, especially as clients navigate updates and system evolutions. Human experts also maintain operational excellence through continuous monitoring (R24) and fine-tuning (R25), ensuring that systems remain adaptive amid shifting business environments. AI systems require this ongoing human judgment to evolve and maintain productivity, particularly when unforeseen changes demand rapid reinterpretation and adjustment of automated outputs.

Finally, ethical AI integration (Case I) emphasizes the need for human oversight to address the challenges posed by AI’s increasing role in organizational operations. R26 highlights that “Human oversight is critical in identifying and mitigating biases that AI systems might inadvertently develop,” stressing the importance of human involvement in ensuring that AI remains fair and transparent. R27 further underscores the need for human professionals to make AI decisions transparent and understandable, allowing for accountability. R28 points out that humans play an essential role in safeguarding privacy and ensuring compliance with data protection regulations, emphasizing that AI systems must operate within legal and ethical frameworks.

4.3. AI and HI collaborative paradigm

As shown in Fig. 4, the integration of AI and HI in the pre-development phase is not merely technical but deeply strategic and ethical in nature. AI’s computational capacity to aggregate and analyze vast datasets enables the detection of latent trends, anomalies, and optimization opportunities across domains such as aviation, healthcare, and logistics. However, this analytical power is inert without the contextual judgment provided by HI. Human actors critically evaluate the implications of AI-generated insights, ensuring that subsequent model development aligns with domain-specific constraints, legal frameworks, and stakeholder expectations. For instance, while AI may suggest a flight schedule optimized for efficiency, human planners must incorporate safety regulations, labor laws, and passenger needs to

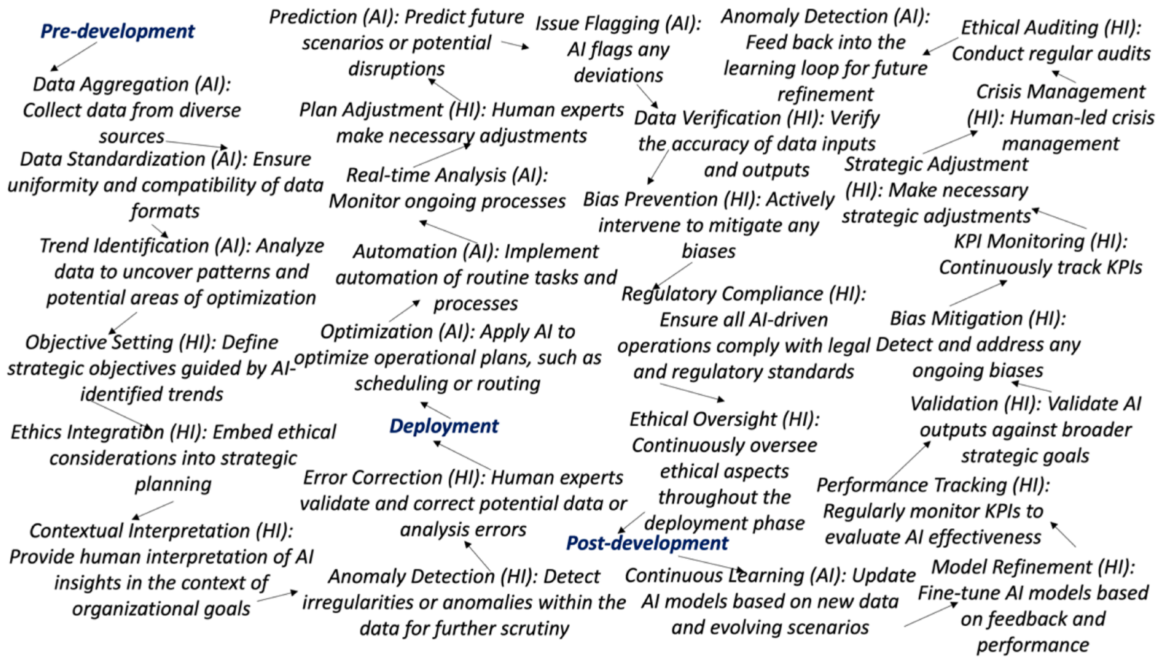

Fig. 4. AI and HI collaborative decision making process (Source: The Authors).

render these insights implementable. Moreover, HI plays a central role in data standardization and quality control. While AI can harmonize formats across disparate systems, humans detect subtleties, such as culturally embedded biases, inconsistent units, or omitted variables, that can critically distort downstream model behavior. Crucially, this stage is also where ethical foresight is embedded into AI design. Human decision-makers define the moral boundaries of algorithmic action, anticipate potential harms, and establish protocols for fairness, transparency, and accountability.

In the deployment phase, the division of labor between AI and HI becomes functionally adaptive, reflecting the temporal and environmental contingencies of real-world operations. AI systems assume a front-line role in automating routine tasks, executing real-time optimizations, and generating data-driven recommendations. These capabilities are particularly salient in high-velocity contexts such as logistics and retail, where systems must adapt to fluctuating demand, inventory levels, or transportation disruptions. However, despite AI's ability to process and act upon high-frequency data, it is HI that ensures decisions remain operationally robust and ethically defensible. Human operators exercise discretion in interpreting AI outputs, adjusting algorithmic parameters, and resolving edge cases that deviate from training distributions. For example, in crisis events such as a natural disaster or geopolitical shock, AI may propose resource reallocations or route changes, but humans assess their feasibility given organizational values, legal liabilities, and socio-political risks. Furthermore, HI plays a critical role in validating AI decisions through continuous monitoring and domain-grounded reasoning. This includes identifying false positives, responding to ethical breaches, and reconciling conflicting objectives across organizational silos. Rather than diminishing the importance of human labor, AI deployment redistributes it, elevating HI to roles of oversight, adaptation, and coordination. The result is not a replacement of human decision-making, but its augmentation within a symbiotic system architecture where strategic flexibility, legal compliance, and ethical responsiveness are maintained through human judgment and interpretive capacity.

Post-development represents a shift from implementation to reflexivity, where the primary concern is not what the AI system can do, but how it evolves, adapts, and remains accountable over time. This phase is characterized by recursive learning, performance feedback, and strategic recalibration. AI systems continue to ingest new data, refine their predictive models, and generate real-time insights. However, without human intervention, these self-learning processes risk entrenching biases, diverging from organizational goals, or creating opaque decision logics. Human experts are indispensable in conducting regular audits, analyzing performance anomalies, and interpreting model drift. Beyond technical correction, HI ensures that AI systems remain anchored in the normative commitments established in earlier stages. This includes updating ethical frameworks in response to new legislation, societal expectations, or emergent risks, such as algorithmic discrimination or data misuse. Human stakeholders are also essential in crisis response, particularly when AI-generated recommendations intersect with public trust, legal accountability, or reputational risk. For instance, in a cybersecurity incident flagged by AI anomaly detection, it is the human analyst who must assess causality, coordinate containment, and communicate with regulators. Moreover, post-development enables organizations to extract meta-insights from system behavior, using AI as a diagnostic tool for broader strategic learning.

5. Discussion

AI and HI collaboration is more productively understood as a dynamic relational process structured across three interdependent dimensions: epistemic asymmetry [94], symbolic accountability [103], and infrastructural interdependence [127]. These dimensions are interdependent and co-evolve to shape organizational approaches to decision-making under algorithmic uncertainty. Collaboration involves integrating computational precision with human judgment while actively managing tensions arising from distinct reasoning logics [87], varying standards of justification [92], and mismatched temporal dynamics [129] between human and algorithmic processes. The motivation for AI and HI collaboration thus stems from the organizational imperative to manage these tensions in a way that safeguards institutional legitimacy, enhances interpretability, and maintains responsiveness amidst increasing technological complexity.

At the epistemological level, collaboration is shaped by persistent incongruence between the statistical abstraction underpinning AI systems and the contextualized interpretive reasoning characteristic of HI. AI models, particularly those grounded in probabilistic inference or deep learning, extract patterns across data streams [20]. However, participants reported that these outputs often lacked semantic specificity or causal rationale unless contextualized through human reasoning [71]. Across cases, human actors did more than validate AI recommendations, they reformulated them in light of domain-specific expectations, situational contingencies, and organizational norms [112]. This distributed mode of cognition, where algorithmic outputs required interpretive framing before becoming actionable, was evident in decision environments characterized by regulatory complexity or operational ambiguity [67]. While the evidence suggests that epistemic coordination can mitigate breakdowns in interpretability, this process remains labor-intensive and potentially inconsistent across contexts, particularly in the absence of structured feedback loops or institutional memory.

The symbolic dimension highlights how collaboration also serves a legitimating function. In domains where decisions affect external stakeholders, legal compliance, or reputational standing, the presence of human oversight provided an important reassurance that algorithmic decisions remained subject to normative scrutiny [91]. Several participants described deliberately foregrounding the “human in the loop” during stakeholder engagement to demonstrate accountability and ethical consideration [4]. Such performative oversight reflects broader institutional expectations that decision systems adhere not only to technical accuracy but also to values of fairness, transparency, and inclusivity [106]. However, our data also indicate variation in how this symbolic function was institutionalized. In some cases, human oversight was informal, ad hoc, or operationally decoupled from the AI’s technical architecture [103]. This variability suggests that symbolic accountability, while effective in maintaining trust, may offer only temporary assurance unless reinforced by formalized governance procedures and stakeholder-inclusive design practices [30]. Moreover, the long-term sustainability of this mechanism remains uncertain in rapidly evolving algorithmic environments [45].

At the infrastructural level, collaboration is mediated through divergent temporal logics and procedural rhythms. AI systems operate continuously, processing live data and adapting through real-time feedback [93]. In contrast, human engagement is episodic, constrained by attentional limits, institutional protocols, and role-based hierarchies [105]. This temporal mismatch often created friction in practice, especially during escalation events or failure recovery. Participants emphasized the importance of infrastructural scaffolding, including predefined override pathways, exception-handling mechanisms, and escalation thresholds, to ensure that human discretion could be exercised effectively [7]. However, such mechanisms were frequently developed reactively rather than systematically. In some cases, iterative adaptation to system failures led to improvements, but these were seldom codified into reusable governance frameworks [15]. As such, while collaboration enabled short-term flexibility and responsiveness, the absence of durable design principles raises concerns about long-term robustness and scalability.

The outcomes of AI and HI collaboration manifest less in optimized performance metrics than in the capacity of organizations to maintain procedural coherence and adaptive resilience under uncertainty. Collaboration supports organizational coherence across diverse reasoning logics and helps prevent both operational fragmentation and excessive dependence on algorithmic decision-making [69]. It supports the creation of decision environments that can accommodate epistemic pluralism, uphold ethical responsibility, and recalibrate authority in response to environmental volatility. This enables a form of conditional stability, one grounded in reflexivity, distributed accountability, and institutional adaptability [19]. Conceptualizing AI and HI collaboration in this way offers a broader theoretical lens for understanding how contemporary decision systems are governed. It invites a shift from viewing collaboration as a means of optimizing outputs to seeing it as a process of institutional co-production [36]. What emerges is a negotiated alignment of logics, expectations, and practices through which decision authority is constituted and sustained. Organizations engaging with AI must therefore design for governance, not just functionality, ensuring that collaborative infrastructures remain attuned to epistemic limits, normative demands, and contextual shifts [108]. This view foregrounds the relational, recursive, and reflexive nature of AI and HI collaboration and offers a foundation for theorizing the institutional conditions under which algorithmic decision systems remain intelligible, legitimate, and responsive to the complexities they seek to navigate [25].

6. Conclusion

This study has employed a multi-case, sensemaking-driven qualitative methodology to investigate how AI and HI interact in real-world operational and supply chain decision-making environments. Drawing on 28 in-depth interviews across nine multinational firms, we developed cognitive maps that captured how decision-makers integrate AI systems into critical business functions such as logistics, warehousing, scheduling, demand forecasting, and risk management. The cognitive mapping process enabled us to trace the evolution of AI and HI collaboration across three key implementation stages, pre-development, deployment, and post-development, revealing how human actors and AI systems jointly construct decision logic under varying conditions of uncertainty, ambiguity, and operational volatility. This empirically grounded approach allowed us to theorize collaboration not as a linear coordination of machine efficiency and human oversight, but as a dynamic sociotechnical process structured by epistemic asymmetry, symbolic accountability, and infrastructural interdependence.

Our findings reveal that the primary organizational motivation for deploying AI systems is not solely cost reduction or productivity enhancement, but the aspiration to create scalable, data-intensive decision processes capable of continuous optimization. Across cases, AI was leveraged to identify latent patterns in high-velocity data environments, generate predictive insights, and automate operational routines that exceed human cognitive limits in terms of volume, speed, and granularity. In contexts such as dynamic routing, demand forecasting, or anomaly detection, AI systems performed particularly well in reducing latency and increasing responsiveness. However, their effectiveness was consistently contingent on high-quality data preprocessing, algorithm calibration, and computational infrastructure, all of which required sustained human input. While AI offered clear advantages in amplifying analytic capabilities, its limitations, most notably in interpretability, causal reasoning, and normative alignment, were also repeatedly surfaced by our participants.

Conversely, human actors retained indispensable roles throughout the AI lifecycle, particularly in tasks that demanded contextualization, discretion, or ethical judgment. The motivation for human involvement was frequently rooted in the recognition that AI systems, though computationally powerful, cannot account for domain-specific exceptions, institutional memory, or shifting regulatory constraints. HI was critical in resolving ambiguities, interpreting edge cases, and mitigating risks associated with over-reliance on opaque algorithms. Moreover, human expertise was vital for identifying errors in algorithmic outputs, integrating stakeholder concerns, and aligning AI actions with strategic priorities and organizational values. However, HI's contribution was also bounded by cognitive load, limited visibility into algorithmic operations, and the increasing complexity of the digital systems they were expected to supervise. As such, while HI introduced resilience and legitimacy into decision-making processes, it also introduced friction, especially when human and machine temporalities and reasoning logics were misaligned.

The evidence across all scenarios highlights that AI and HI collaboration is deeply embedded in the infrastructures, organizational setups, and normative systems that shape decision-making. Such collaboration works best when supported by flexible governance frameworks that can coordinate different ways of thinking and timing between humans and machines. For example, in crisis situations, AI systems can rapidly generate optimization strategies, but it is the human agents who interpret these suggestions, assess their legal, ethical, and reputational implications, and make the final judgment. Furthermore, post-deployment phases revealed that the long-term sustainability of such collaboration depends on continuous learning, cross-functional alignment, and regular performance evaluation, functions that cannot be fully automated. This dynamic and co-constitutive form of collaboration, which we term institutional co-production, goes beyond traditional models like "human-in-the-loop" and "AI-assistance." Rather than viewing humans as mere overseers or AI as passive tools, institutional co-production reflects a more adaptive, relational approach to decision-making under algorithmic uncertainty. Nonetheless, this model also faces key limitations. AI systems often struggle with contextual understanding, especially in culturally or socially tasks. Their effectiveness is tightly linked to the quality, diversity, and reliability of data. In settings where data is outdated, biased, or incomplete, AI outputs may be misleading or unfit for practical use. Additionally, data privacy and security concerns can restrict information flow, hindering collaboration. Even when AI tools are technically advanced, organizations may lack the readiness to implement them meaningfully. Effective collaboration requires more than just technological capability, it demands strategic alignment, workforce training, and governance structures that can respond to evolving needs and risks. Without these, there is a danger of siloed decisions or overreliance on flawed outputs. To strengthen AI and HI collaboration, organizations should prioritize robust data governance, ensure privacy and security, and develop adaptive systems that support ethical, context-sensitive, and accountable decision-making.

This study makes a theoretical contribution by introducing the concept of institutional co-production to describe how humans and AI systems work together in real-world decision-making. Unlike traditional models such as "human-in-the-loop" or "AI-assistance", which often assume fixed roles, where humans supervise and AI supports, we show that collaboration between humans and AI is more dynamic and shaped by the organizational and institutional context. In practice, humans and machines do not simply pass tasks back and forth. Instead, they constantly adjust to each other based on how decisions are made, who is accountable, what kind of data is available, and what risks are involved. This process is influenced by factors such as organizational rules, professional norms, legal frameworks, and infrastructure constraints. To explain this complex interaction, we bring together ideas from three theoretical perspectives. From distributed cognition, we highlight how thinking and decision-making are shared between humans and AI. From institutional theory, we focus on how norms and rules shape how humans interpret AI outputs and decide whether or not to act on them. From sociotechnical systems, we view AI as part of a broader system that includes people, processes, and technologies. Our study combines these views to show that collaboration is not just about designing smart machines, it is also about building systems where AI can be trusted, used properly, and held accountable. This perspective helps us better understand why AI tools sometimes fail in practice, even when technically advanced. It also shows that successful AI and human collaboration relies more than the technology itself, but on the organization's ability to support learning, build trust, ensure ethical oversight, and adjust to changing situations. In this way, our study expands existing theories by showing that the relationship between humans and AI is not fixed, but constantly negotiated within institutions. This helps future researchers and practitioners design systems that are not only efficient, but also socially and ethically robust.

While this study offers a rich account of AI and HI collaboration within OSCM contexts, several limitations warrant consideration. The findings are based on 28 interviews across nine benchmark firms recognized for their AI adoption; while diverse, this sample may not fully reflect sectoral variation or differences in technological maturity across regions. The analysis primarily captures the perspectives of key HI actors, operations managers, data scientists, and AI system designers, but future research could benefit from incorporating insights from end-users, policy-makers, and other ecosystem stakeholders. Moreover, the study's cross-sectional design limits our ability to observe how collaboration evolves over time, particularly in response to failure events, system upgrades, or regulatory interventions. Addressing these limitations, future research should deepen this relational framing by exploring intra-AI collaboration, how multiple AI systems with divergent learning logics are orchestrated and mediated by human actors within shared decision ecologies. As AI ecosystems become increasingly modular, decentralized, and heterogeneous, the complexity of human–machine collaboration may exceed current governance capabilities. Understanding how HI intervenes at critical interfaces to structure accountability, negotiate ambiguity, and manage escalation processes will be essential. Longitudinal studies are especially needed to trace the evolution of collaborative infrastructures over time, capturing how organizations learn from disruptions, adapt to regulatory shifts, and institutionalize reflexive governance. By laying this foundation, the present study contributes toward building more sustainable, intelligible, and ethically responsive models of AI–HI integration in complex organizational systems.

Ethics statement

This study was reviewed and approved by the Cardiff University Business School Research Ethics Committee under approval number 812, dated 06 July 2022. All participants were informed about the purpose of the study and provided their consent before participation. The study ensured the confidentiality and anonymity of all participants, and they were given the option to withdraw from the study at any point without penalty. No personal identifying information was collected during the study to ensure the privacy and security of the data.

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CRediT authorship contribution statement

Xinyue Hao: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Resources, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Emrah Demir:** Writing – review & editing, Supervision, Methodology, Data curation, Conceptualization. **Daniel Eyers:** Writing – review & editing, Supervision, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A

About the interviewee and the company

1. Can you briefly introduce yourself, your position and experience, and your responsibilities?
2. What applications does your company provide to business or customers? In which industries? And in which sectors of the supply chain?

Early development:

1. What are the external and internal factors that affect the application of AI and HI in supply chain decision-making?
2. What are the benefits, potential and real, of using the collaboration of AI and HI in supply chain decision-making?
3. What are the challenges, potential and real, of using the collaboration of AI and HI in supply chain decision-making?
4. What function do AI and HI serve in your supply chain decision-making contexts? How was the task performed in the past, before using AI in decision-making?
5. How did you evaluate the scenarios and select AI and HI in supply chain decision-making? Did you consider implementing alternatives other than AI or the combination of AI and other technologies?
6. How did you decide that the specific algorithm or model and expert knowledge would be suitable for the selected applications? Which characteristics did you consider (e.g., data volume, features, cost, precision, experience, risk, explainable etc.)?
7. What are the critical success and failure factors when integrating AI and HI in collaboration?

Piloting:

1. What kinds of experiments/simulations did you conduct before the implementation of AI-HI decision-making in supply chain?
2. What was the purpose of conducting experiments/simulations?
3. What were the unintended/supering outcomes of your experiments/simulations?
4. What were the blind spots associated with using AI and HI decision-making in supply chain that you discovered through the pilot projects?

Implementation:

1. How did you manage the implementation of AI and HI decision-making in specific contexts?
2. How did you deal with national/governmental/organizational characteristics for the implementation of AI and HI in supply chain decision-making?
3. How did you coordinate AI and HI implementations with the upstream and downstream of algorithms developing? To what extent were they involved?
4. Have you experienced a failure during the implementation? If so, how did you manage it?

Acceptance of deliverables:

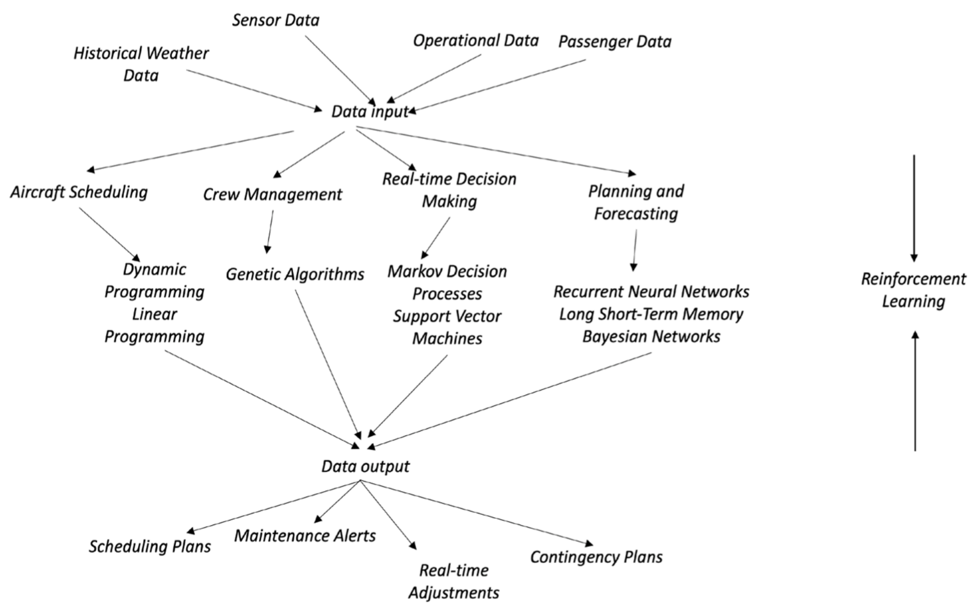
1. What are the measurements of AI and HI decision-making performance?
2. What are the potential AI and HI decision-making accountability mechanisms?
3. How to improve the results of AI and HI decision-making in the following projects?

Future application:

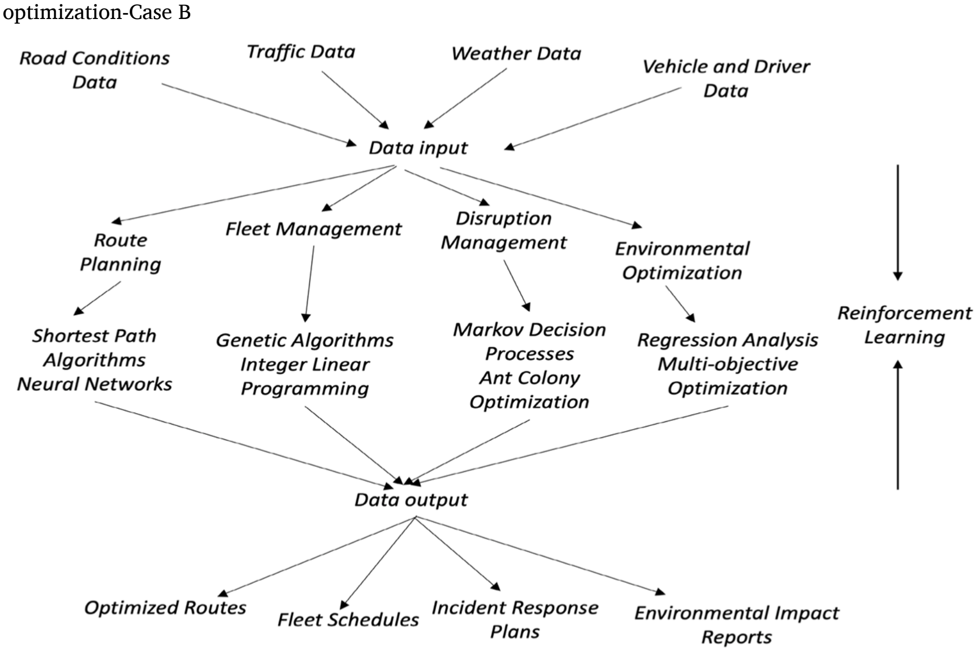
1. Do you plan to expand the application of AI in tactical and strategical decision-making levels?
2. What other future developments can you foresee the AI technology in supply chain decision-making? Which industries will grow faster? What are the associated potentials and barriers?

Appendix B

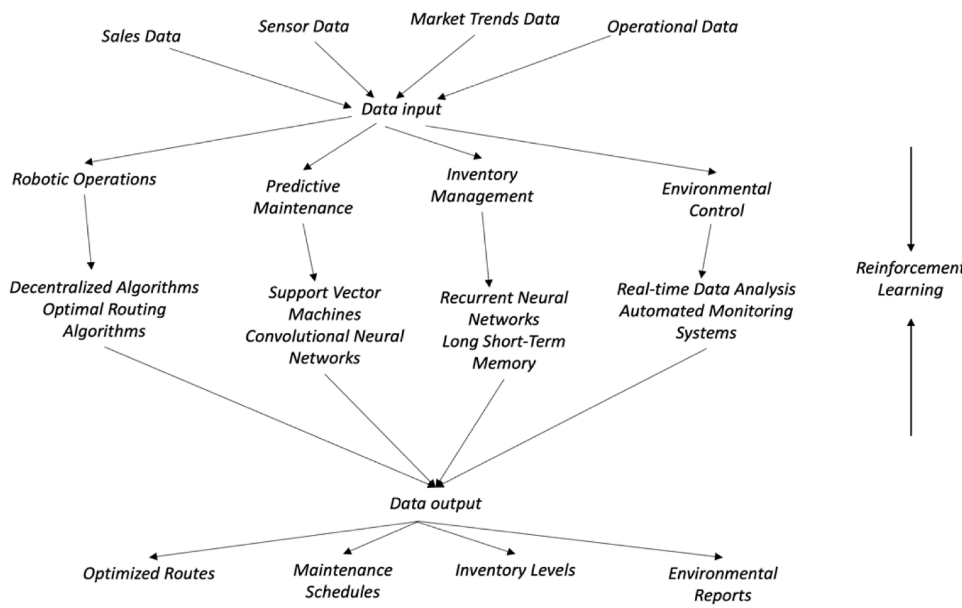
Scheduling and planning-Case A



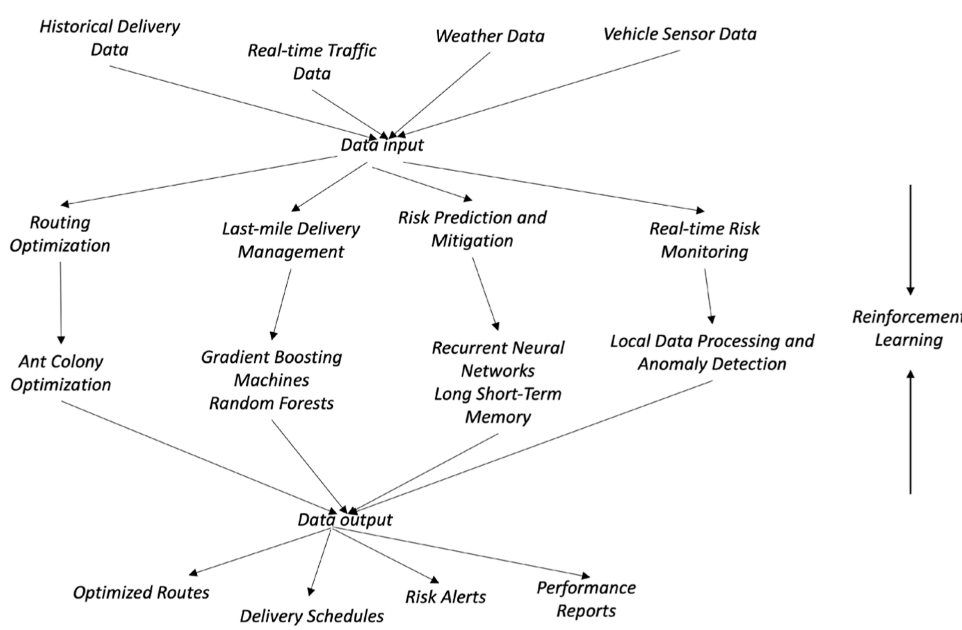
Logistics and route optimization-Case B



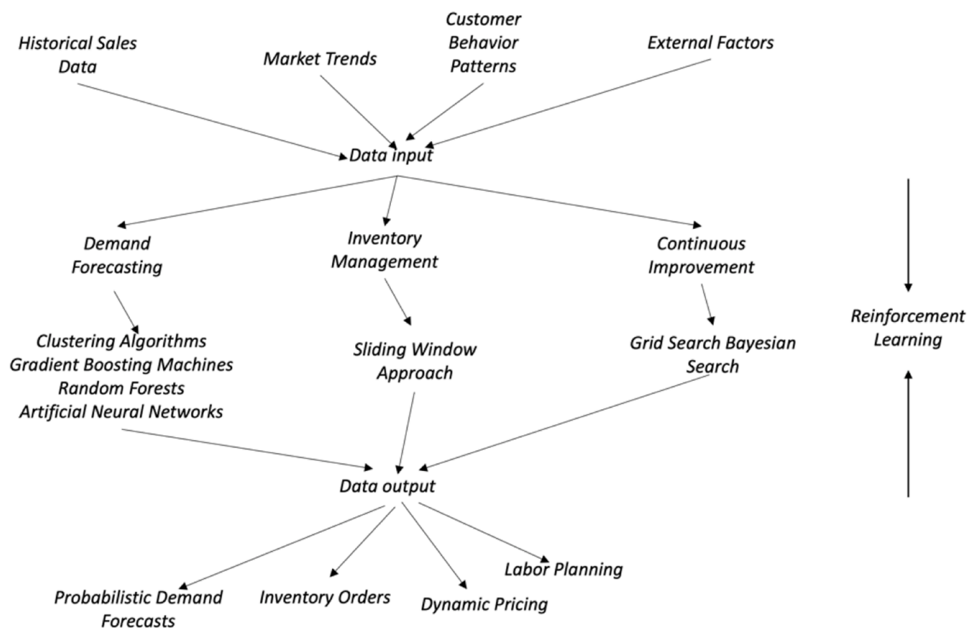
Automated Warehousing-Case C



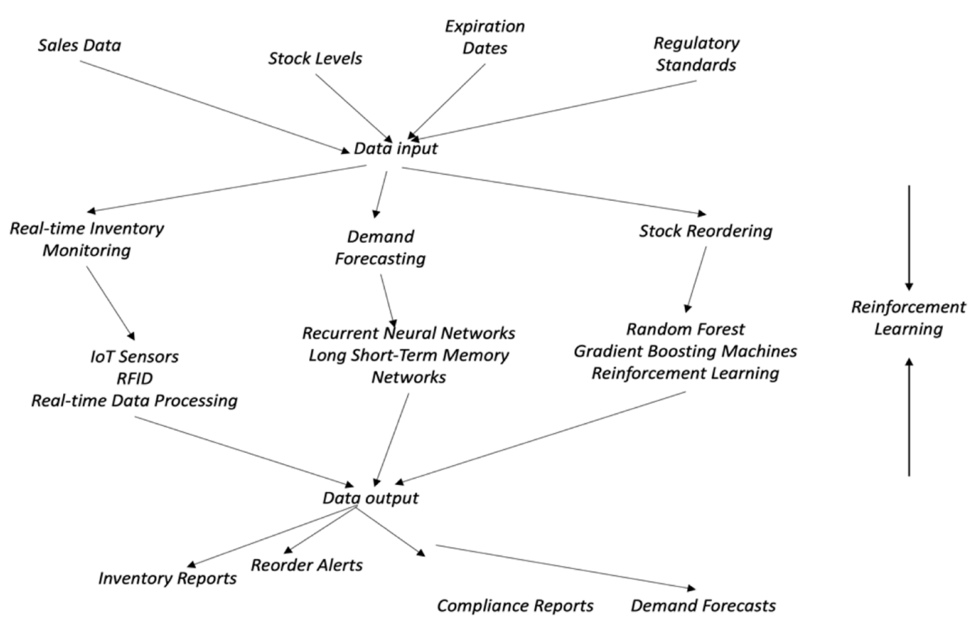
Risk management of logistics-Case C



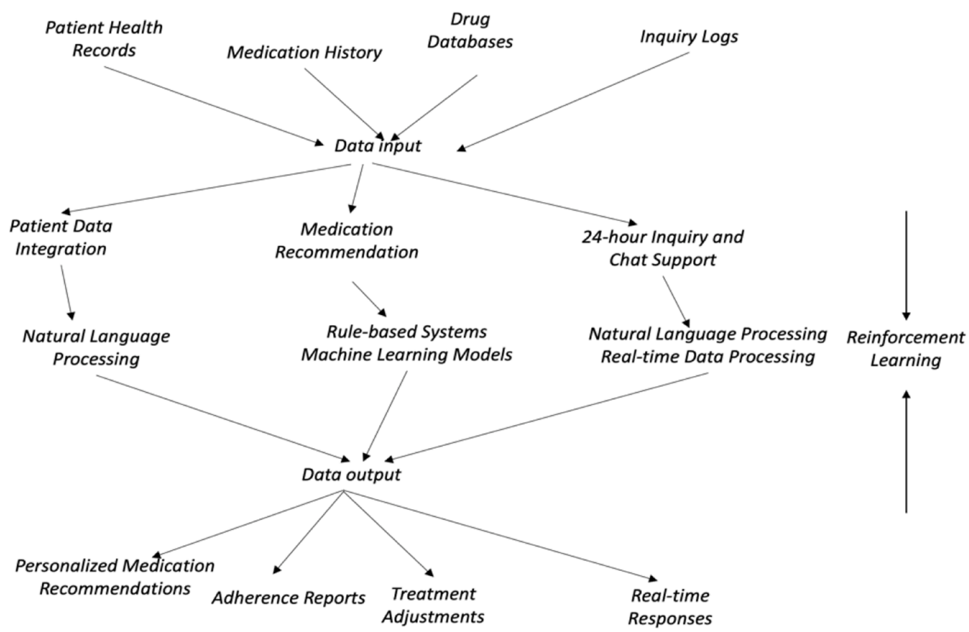
Demand forecasting-Case D



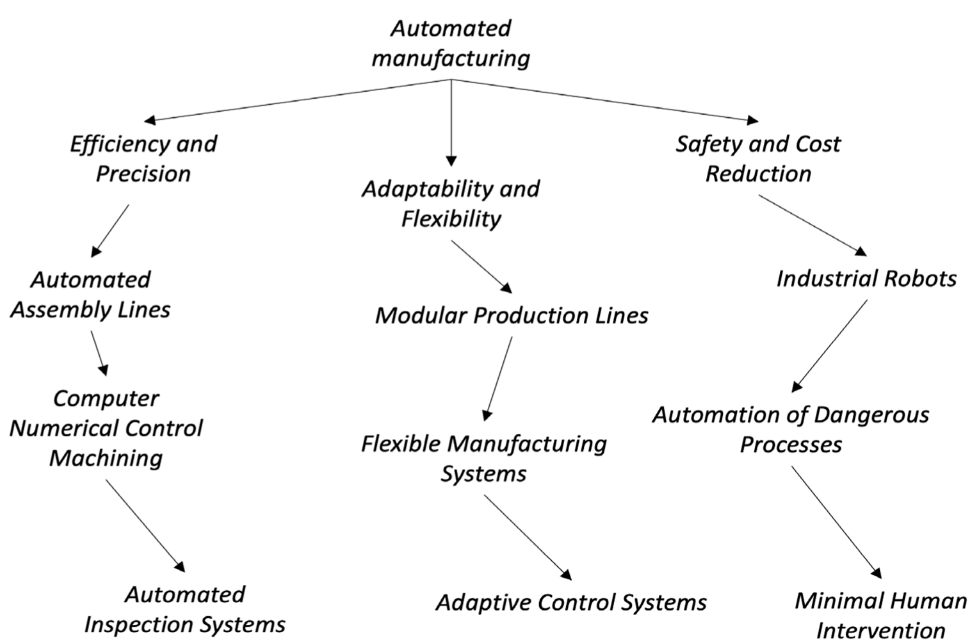
Inventory optimization-Case E



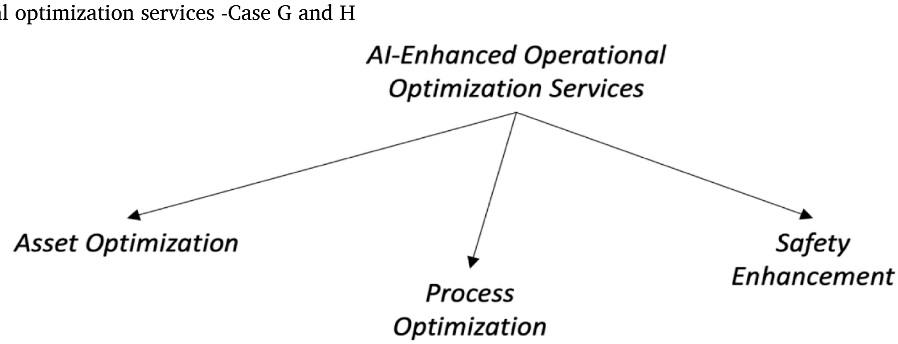
Recommendation and decision support-Case E



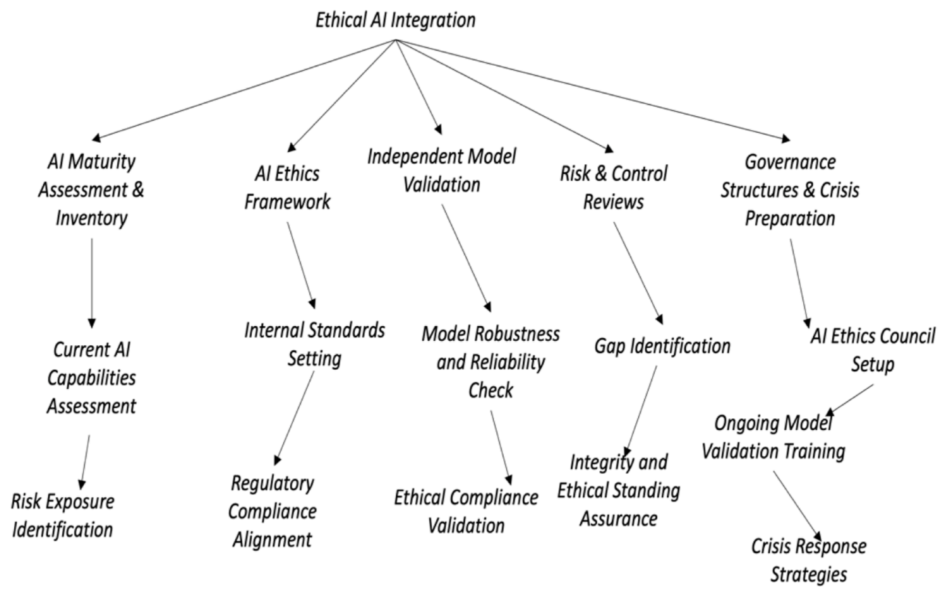
Robotics and manufacturing-Case F



AI-enhanced operational optimization services -Case G and H



Ethical AI integration services-Case I



Data availability

The data that has been used is confidential.

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