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ORIGINAL RESEARCH

Human-artificial intelligence collaboration in supply chain outcomes: the mediating role of responsible artificial intelligence

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Abstract

Human-artificial intelligence collaboration (CAIT) presents considerable opportunities for optimising supply chain outcomes. Nonetheless, it poses numerous ethical, technological, and organisational obstacles that could impede its efficacy. This study contends that responsible AI (RAI) systems can function as a conduit between CAIT and supply chain outcomes to tackle these challenges. Accordingly, we leveraged the resource-based view (RBV) and socio-technical system (STS) theoretical lenses to analyse the mediating role of RAI in the relationship between CAIT and two supply chain outcomes (supply chain wellbeing (SCWB) and sustainable business performance (SBP)). The suggested model was evaluated using PLS-SEM on survey data from 301 supply chain managers in the UK. Our analysed data revealed a statistically insignificant relationship between CAIT and supply chain outcomes (SCWB and SBP). However, the mediating role of RAI was confirmed. The findings suggest that CAIT is merely a component of a supply chain's capacity to produce intrinsic resources, rather than a universal solution. To harness the dividends of human-AI collaboration involves designing boundaries, aligning CAIT to supply chain goals and integrating ethical and transparent strategies. Our findings contribute to the discourse on AI use in supply chain literature by showing that CAIT can influence supply chain outcomes by bridging ethical, operational and technological gaps while fostering trust and efficiency.

Keywords Supply chain well-being · Sustainable business performance · Socio-technical systems theory · Responsible AI · RAI · Human-AI collaboration · Resource-based view

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1 Introduction

Due to increased and unpredictable disruptions, SCWB as a multifaceted and dynamic concept offers a comprehensive approach to managing supply chains (SC) (Vann Yaroson, 2024). It measures the overall health of the SC and encompasses the simultaneous building of resilience, navigating physical, emotional and social factors, incorporating external economic factors, and managing global supplier networks. Sustainable business performance (SBP) on the other hand requires a firm to integrate sustainability's societal, environmental, and economic values (Kamble et al., 2020) for competitive advantage. These multidimensional constructs are inherently complex supply chain (SC) outcomes that require addressing competitive priorities which may be challenging to manage.

Artificial intelligence (AI), defined as a form of machine intelligence that can learn and adapt to various scenarios (Abedin et al., 2022), has emerged as a critical resource that may foster SC outcomes through its predictive and analytical capabilities (Queiroz et al., 2021a). It stems from the technology's ability to analyse rich datasets for effective decision-making. Data-driven businesses and SC firms have begun using AI-related technologies for effective decision-making, to gain competitive advantages, and to build resilience (Belhadi et al., 2021). For instance, Amazon has leveraged AI-powered predictive forecasting to address unprecedented demand, while UPS uses its AI-driven algorithm, ORION, to track and optimise last-mile delivery (Chawla, 2024). A survey by McKinsey (Chui et al., 2022) demonstrated that AI-powered SC facilitated inventory management processes by 65% and reduced costs related to logistics by about 15%. Similarly, Gartner (2024) predicted a 40% compound growth in AI-related investment between 2018 and 2024 as firms expect increased automation integration in their SC processes. AI, thus, improves SC operations and sustainability practices by harnessing existing resources and building collaborative processes.

Nonetheless, a common association exists between AI-powered technologies and issues such as data transparency, discrimination, algorithmic output interpretability (Mikalef et al., 2022), bias, and the potential to maliciously exploit AI (Arrieta et al., 2020). An important concern arises from the potential bias of AI algorithms, which may generate unfair results based on historical data (Charlwood & Guenole, 2022). AI-driven supplier selection, for example, may overlook risk-prone suppliers or make biased decisions based on historical data. Additionally, the ethical implications of AI-related technologies complicate the enforcement of regulations and accountability (Ashok et al., 2022). For instance, a survey by Secondmind (2024) showed that over 80% of US SC decision-makers have been left frustrated by AI-powered tools when employed during a disruption. This is especially true when it comes to SC's decision-making capabilities (Munoko et al., 2020). Hence, the use of AI-related technologies for decision-making may result in bias, which may lead to inadequate understanding of the environment, ineffective risk management techniques, or flawed supplier selection processes. These challenges have raised concerns about the efficacy and potential integration of AI-powered technologies into managing SC outcomes. It also implies that managing AI-related technologies transcends engineering design and algorithmic potential to include societal and political concerns.

Scholars have alluded to the importance of human-AI collaborative strategies (CAIT) in strengthening AI use for successful business outcomes (Jiang et al., 2023). CAIT refers to the process of developing socio-technical systems in which humans and AI collaborate in a mutually beneficial manner (Loske & Klumpp, 2021). It transcends human-AI interaction to involve goal congruence, proactive task management and strategic alignment in tracking progress. CAIT's core premise lies in the social interactions between human judgement and emotional intelligence with AI systems' computational power to mitigate any associated risks (Simon et al., 2024). This unique synergy of human agents and AI enhances productivity, decision-making and innovation across SCs. Several challenges inhibit CAIT design and may affect performance (Johnson & Vera, 2019). These include information asymmetry, deciding the boundaries of human and AI responsibilities, distrust of AI systems by humans, especially with limited transparency, absence of skills and training, and the perpetuation of bias by AI systems if training data is flawed (Petrescu & Krishen, 2023). This has led to calls for best practice recommendations, particularly in making AI responsible for human-AI collaboration for supply chain operations.

Making AI responsible (RAI) entails that AI tools operate ethically, fairly and accountably (Mikalef & Gupta, 2021). The idea of RAI, while still in its infancy, is primarily intended to help decision-makers understand the actions of an AI system, its output, and the principles that underlie these outputs (Chowdhury et al., 2022a). The ability to obtain explanations for the output that the AI system produces will lessen biases associated with SC operations (Modgil et al., 2022). There are, however, fragmented approaches to the design and deployment of RAI systems. While some studies suggest that tackling bias is key, others posit that it is necessary to fundamentally alter the way RAI is approached to achieve successful business outcomes using AI-powered systems (Felzmann et al., 2019). It thus implies that to achieve SCWB and SBP using AI-powered systems, it is necessary to fundamentally alter the way RAI systems are designed and deployed.

In this study, we advocate that CAIT strategies can leverage RAI systems to achieve successful SC outcomes (SCWB and SBP). We also opine on the use of CAIT as a practical approach to the design and deployment of RAI systems. These scenarios require integrating employees' knowledge and expertise with AI systems to significantly influence how an organisation's explainable and transparent AI systems are perceived (Kong et al., 2023). There is still limited empirical understanding of the mechanisms through which human-AI collaborative strategies create successful business outcomes. The paucity of studies in this direction has resulted in a lack of understanding about the potential of human-AI collaboration and leaves practitioners in uncharted waters when faced with such applications in their supply chains. To obtain any meaningful theoretical and practical implications and identify critical future research agendas, it is pertinent to understand how human-AI collaborative strategies result in successful business outcomes (Toorajipour et al., 2021). Building on the concept of CAIT, this study aims to answer two closely related research questions:

(1) Does human-AI collaboration result in enhanced SC outcomes (SCWB and SBP)?
(2) If so, do human-AI collaborative strategies enhance the relationship between CAIT and SC outcomes through their effect on RAI?

To answer these questions, we ground our study theoretically on the resource-based view (RBV) and socio-technical systems theory (STS). Our aim is to address this knowledge gap and advance SC literature by drawing on existing studies that suggest a potential value generation that involves the use of human-AI strategies (Chowdhury et al., 2022a). Additionally, we investigate the mediating function of RAI predicated on the idea that the use of AI systems in SC operations requires that they be ethical, transparent and aligned with human values. Also, by investigating the mediating function of RAI, we confirm the potential of human-centred approaches in strengthening RAI principles through contextual understanding and human judgement. The contribution of this study is twofold. Primarily, it shows the direct impact of CAIT on the identification of human values in RAI design. The results enrich both AI and STS literature by empirically confirming that firms' intrinsic resources and socio-technical interactions to effectively deploy human-AI strategies may favour RAI systems. Secondly, our study contributes to SC literature by demonstrating that CAIT impacts SCWB and SBP indirectly by stimulating SCs to proactively combine the efficiency, data processing capabilities and predictive power of AI with human creativity, ethical judgement and strategic decision-making.

An overview of the paper is provided in this section. Section 2 presents the literature review, followed by the theoretical foundation, hypotheses, and conceptualisation of the study, followed in Sect. 3. The study's methodological approach and findings are presented in Sects. 4 and 5, respectively. We discuss the results and their implications in Sect. 5. The conclusions and limitations of the study are outlined in Sect. 6.

2 Literature review

This section explores the literature on human-AI collaborative strategies (CAIT) (2.1), supply chain well-being (SCWB) (2.2), sustainable business performance (SBP) (2.3), and (2.4) the mediating role of responsible AI and the integrated RBV and STS theories to explain the link between these ideas (2.5).

2.1 Human-AI collaborative strategies (CAIT)

CAIT describes the process of developing socio-technical systems in which humans and AI collaborate in a mutually beneficial manner to achieve desired outcomes (Loske & Klumpp, 2021). It transcends human-AI interaction to involve goal congruence, proactive task management and strategic alignment in tracking progress (Haresamudram et al., 2023). CAIT is exhibited when interactions between humans and machines are concise and devoid of manipulation. By combining human judgement and emotional intelligence with AI-powered systems' computational power, advocates of CAIT believe that the associated risks and limitations of AI use are mitigated (Kong et al., 2023). An example of human-AI collaborative efforts is Swarm AI, based on the swarm intelligence found in biological systems that supports faster decision-making (Metcalf et al., 2019). Swarm AI has demonstrated better predictions than machine learning predictions as its AI algorithms are trained on identified behaviour, and individuals' application of tacit knowldge to AI algorithms and decisions (Jarrahi et al., 2023). Thus, the unique synergy of humans and AI is expected to enhance productivity, decision-making and innovation across SCs.

For successful business outcomes, some authors emphasise the need to accurately design the AI pipeline to achieve CAIT (Thakkar, 2024). Others categorise CAIT as a subcategory of human-AI transparency (Felzmann et al., 2019), which includes the interactions and overlapping of AI system transparency and user transparency as presented in Fig. 1. In this regard, transparency of AI systems involves bidirectional open access and explanations of algorithmic models between systems and stakeholders (designer, regulatory and user). User transparency includes norms and morals that directly or indirectly shape AI use and the underlying regulations framing (Haresamudram et al., 2023). Human-AI collaborative strategies, thus, involve strategically and effectively harnessing these elements of AI's ecosystem, a process that is still evasive in the literature.

That notwithstanding, CAIT is based on three principles, which include the demand for the collective efforts of humans and AI systems; open and cooperative action involving all stakeholders; and non-manipulative and openly available information. These principles suggest that AI system creators have a latent influence on AI itself and that social norms

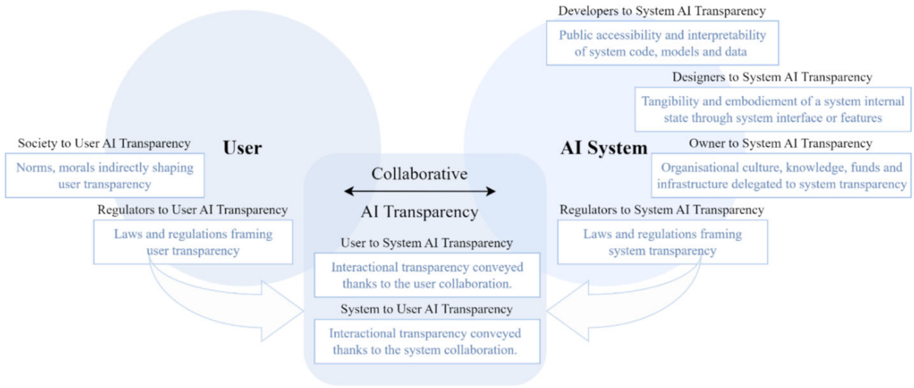

Fig.1 CAIT and AI transparency subcategories

have an indirect impact on user behaviour. In addition, collaborative strategies for human-AI interactions, therefore, are dependent on collaborators' mobilised resources, available technology and technical expertise to ensure that AI systems function well within a consortium (Flyverbom, 2016). Also, to attain the intended outcomes, it is necessary to have improved governance and oversight (Flyverbom et al., 2015). It therefore positions CAIT as an intrinsic resource and a socio-technical system, distinguishing it from existing considerations of human-AI interactions and demonstrating its bi-directional, multipartite and collaboration-focused features.

2.2 Supply chain outcomes (SCWB and SBP)

Supply chain well-being (SCWB) is a comprehensive approach to assessing the overall health of a SC. Its focus is on achieving a balance between operational excellence and ethical consideration of all SC stakeholders (Vann Yaroson et al., 2024). SCWB's fundamental elements include the economic performance of the focus firm and its surroundings, due diligence, risk and resilience, supplier relationships, employee satisfaction and sustainability. It concerns SC performance (Mishra et al., 2022) with emphasis on structures erected to curb human rights issues (Wenzel et al., 2019), due diligence (Verma et al., 2023), resources conservation, external economic influences (Mariados et al., 2016), and long-term supplier relationships (Wang & Zhao, 2023). The interaction of these components facilitates the effective functioning of a SC while taking into account the ethical, physiological, and physical welfare of its supply chain partners. SCWB reflects the emerging recognition of SCs as ecosystems of human and ecological interactions (Wieland, 2021).

Tenets of SCWB opine that its comprehensive approach addresses issues of trade-offs where managers must prioritise specific elements of their SC (Negri et al., 2022). For example, some managers focus on building resilience and viability (Ivanov et al., 2021), others on sustainability (Govindan et al., 2020), while others focus on SC partnerships (Dahlmann et al., 2019). Efficiency in some parts of the SC often leads to trade-offs and does not denote SCWB. A resilient SC with poor sustainable practices and a failing economic environment may threaten its well-being. Thus, SCWB follows the survivability agenda of Ivanov (2022), which advocates for an integrated approach to SC operations and extends existing studies that have examined these vital factors individually (Jabbarzadeh et al., 2018). Given this, we argue for SCWB to facilitate effective SC management practices.

Similarly, sustainable business performance (SBP) is a multidimensional concept that involves a firm's ability to integrate sustainability's societal, environmental, and economic values (Chung et al., 2021). It focuses on organisations' ability to offer products and services profitably while ensuring business continuity with minimal environmental and societal harm (Gong et al., 2018). Due to stakeholders' growing interest in environmental preservation and quality of life, firms attempt to integrate sustainability practices in their decision-making frameworks for competitive advantage (Fernando et al., 2019). The societal dimension focuses on the firm's reputation and long-term relationship with its stakeholders (Sharma et al., 2020), including fulfilling the needs of its employees, customers, and the public. The economic dimension of sustainability aims at improving a firm's financial performance relative to competitors (Khan et al., 2021). The environmental side seeks to minimise harmful ecological effects, including waste reduction and carbon emissions (Chowdhury et al., 2022b).

Managing these SC outcomes may be challenging. For instance, ensuring consistency in SCWB practices across diverse suppliers and SC partners spanning multiple countries with diverse cultural, legal and regulatory standards may be difficult. In SBP, goal alignment may be problematic as firms are required to balance their short-term profitability goals with long-term sustainability objectives. For instance, profit margins and cost pressures may conflict with investments in sustainability initiatives which may lead to trade-offs that are challenging to navigate. Measurement and accountability present challenges, as SCWB and SBP (Mio et al., 2022) may not be readily quantifiable, complicating the progress tracking and the enforcement of standards. These elements collectively render SCWB and SBP concepts that require substantial resources, dedication, and strategic alignment for effective management.

AI-powered models have been suggested as effective in managing SC networks (Zamani et al., 2022), SBP (Ghobakhloo et al., 2021; Naz et al., 2021), supply chain resilience (Modgil et al., 2022), and well-being (Vann Yaroson et al., 2024). However, the negative connotations of AI use, including the lack of transparency in its design and deployment, have resulted in stakeholders feeling cautious and sceptical. The absence of transparency can diminish the visibility of suppliers' operations, heighten risks by obscuring the understanding of operational processes, give rise to trust concerns, and present challenges in meeting compliance requirements. The concept of CAIT is expected to address these shortcomings by highlighting the importance of collaborative strategies between humans and AI systems that increase transparency through building RAI systems. The limited availability of empirical research on CAIT and SC outcomes presents an underlying motivation for our study.

2.3 Responsible artificial intelligence (RAI)

Responsible AI (RAI) is the idea that ethical, moral, and societal principles should be considered when designing and using AI-related technologies. Emerging as a solution to associated AI challenges (Constantinescu et al., 2021), RAI offers several elements to developing safe and trustworthy AI systems (Mikalef et al., 2022), including explainability (Arrieta et al., 2020), accountability (Raja et al., 2023), and fairness (John-Mathews et al., 2022). Although these approaches offer practical guidance for RAI design, their fragmented nature presents a quagmire for AI users. There have been calls for a more holistic approach to RAI design and deployment (Dignum, 2019). To this end, the Alan Turing Institute published a report proposing a set of ethical principles (fairness, accountability, sustainability, and transparency) referred to as the FAST model (Leslie et al. 2019) as a practical approach to achieving RAI.

In the design of RAI from a holistic perspective, each principle addresses certain aspects of the ethical dilemma of AI. AI accountability addresses the associated dangers of creating and making decisions that are unjustifiable and/or illegitimate (Arrieta et al., 2020). It focuses on the justification of intentions, motives, and rationales for AI decisions (Mikalef et al., 2021; 2022). AI accountability strongly relates to AI systems' interpretability and the ability to monitor decision-making processes from the black box system (Wieringa, 2020). Here, the public helps identify, interpret, and evaluate the behaviour of an AI system. It implies that the design and deployment of AI-related technologies should be continuously accessible, recorded, analysed, and monitored using a defined protocol (Leslie, 2019). The principle of AI fairness focuses on reducing unfair consequences, user discrimination, and misjudgement of specific user groups using algorithms and data in operations (Memarian & Doleck, 2023). Non-discrimination forms the bedrock for AI fairness (John-Mathews et al., 2022). The sustainability context of RAI pertains to incorporating environmental, societal, and individual considerations into the design and deployment of an AI system. This is done to minimise any negative impact on these aspects of sustainability dimensions that support and promote the long-term welfare and goals of users (Larsson et al., 2021).

Despite the agitation for the design and deployment of RAI systems, there is less information available on their implementation and use in SC operations. For instance, it is unclear how incorporating fairness into an AI system specifically addresses biases in supplier selection or enhances interpretability for decision-making in SCs. Therefore, this study proposes that incorporating collaborative techniques into human-AI interactions is an essential resource for the design and implementation of RAI systems. This, in turn, helps achieve the aims of SC outcomes, including SCWB and SBP. In line with the RBV and STS theories, this study suggests that CAIT, as an organisation's intrinsic resource, leads to favourable SC outcomes. However, human–machine socio-technical interactions that result in a holistic deployment of RAI (fairness, accountability, and sustainability) mediate these relationships. Sociotechnical interactions are essential for human and AI systems to work well together. These interactions create holistic RAI systems that support organisations in achieving their goals, such as SCWB and SBP.

2.4 Theoretical lens

Our theoretical framework is predicated on the ideas of social-technical systems (STS) and the resource-based view (RBV). RBV, as a theoretical framework, explains how firms use their resources to achieve competitive advantage and maintain integrity in various environments (Barney, 1991). The underlying notion is that a firm's competitive edge is dependent on its unique tangible and/or intangible assets, often characterised as valuable, scarce, inimitable, and non-substitutable (Collis & Montgomery, 2008). From this perspective, a firm's ability to efficiently leverage these resources can be a source of significant business value. In essence, resources are the inputs that facilitate a firm's transformation process to achieve favourable outcomes (Madhani, 2010). Human-AI collaborative strategies are considered unique resources that organisations need to understand for effective implementation due to their processing capabilities (Chowdhury et al., 2023). Nevertheless, merely implementing these technologies in business operations does not guarantee that firms and SCs will gain a competitive edge. For resources to translate to competitive advantage, they must be effectively harnessed. A firm's socio-technical capital is distinctive, based on organisational dynamics, culture, and human practices materialised through technologies. The ability to strategically harness human-AI collaborative interactions to achieve business outcomes demonstrates CAIT as an intrinsic resource (Haresamudram et al., 2023). Developing these strategies is complex and requires a significant commitment from all involved stakeholders to maintain mutually beneficial outcomes. As such, CAIT represents an inimitable and non-substitutable combination of human, cultural, and knowledge resources that are unique, rare, and non-substitutable for an organisation. It also suggests that as technologies evolve, businesses that embrace human-AI collaboration will be better positioned to navigate future challenges and capture new opportunities. CAIT has been studied in nexus requiring satisfactory business outcomes, including employee well-being (Chowdhury et al., 2023), organisational performance (Przegalinska et al., 2025), sustainable business performance (Bag et al., 2021) and SC operations (Loske & Klumpp, 2021). While CAIT itself is considered a resource, it is not inherently a source of competitive advantage until it has been effectively harnessed to a capability. By effectively leveraging the design of human-AI collaborative strategies, this resource can be transformed into a valuable capability that drives sustainable business outcomes.

STS theory, as posited by Applebaum (1997), explains how societal elements (users, decision-makers, designers, and regulators), technical systems (technological resources) and technology-driven processes are connected to achieve intended business outcomes. The objective is to strategically harness the benefits of collaborating with humans and machines for competitive advantage and business performance. Extant literature considers human-AI collaboration a socio-technical system (STS) (Chowdhury et al., 2022a), which posits that humans collaborate with technologies to eliminate obstacles (Przegalinska et al., 2025). This collaboration occurs not only through interactions between AI systems and users but also between AI and its developers, regulators, and business owners (Fig. 1). In our study, we portray CAIT as a collaborative process that involves the socio-technical interaction between systems, their developers, and end users. It is not limited to a narrow perspective but includes broader stakeholder interactions. We examine how humans and systems function as STSs to provide complete and accurate information (Larsson & Heintz, 2020). STSs also play a crucial role in enhancing RAI, which is an important aspect of human-AI collaboration in creating valuable business outcomes (SBP and SCWB) (Ananny & Crawford, 2018).

Therefore, our narrative advocates for using STS theory to frame CAIT as a socio-technical partnership between humans and AI systems to promote responsible AI (RAI). This includes measures of AI accountability, fairness, and sustainability. We empirically test CAIT as a socio-technical intrinsic resource that facilitates holistic approaches to designing and deploying RAI (accountability, fairness, and sustainability) to achieve favourable business outcomes (SBP and SCWB).

2.5 Knowledge gaps

Current scholarship suggests that collaboration between humans and AI systems can yield favourable business outcomes, such as increased efficiency, improved responsiveness, and enhanced decision-making (Chowdhury et al., 2022a). However, these intersections are still emerging, which present several knowledge gaps. For instance, the boundary-spanning AI-driven decision-making and human roles in SC operations remain scarce in the literature (Hermann and Huang, 2020). It is also unclear how biases in AI algorithms influence SC decisions and affect human well-being, as algorithms have not been developed to assist collaborative processes. This may invariably suggest that CAIT is an emerging theme in SC management literature that requires both theoretical and empirical investigations to better understand the elements that influence these symbiotic linkages in SC operations.

Further, the literature has progressed from exploring AI adoption propensity by stakeholders and its accrued dividends in SC operations to understanding how to successfully implement these technologies (Tsolakis et al., 2023). There has also been a growth in literature on the associated ethical implications of human-AI collaborative strategies (Boni, 2021). Thus, highlighting the importance of CAIT (human intuition and judgement and AI-powered analytical tools) for favourable business outcomes. However, there is a paucity of empirical evidence to support the implementation process and how these factors address AI strategy. There is also a lack of theoretically grounded research models and frameworks to understand human-AI collaborative strategies in SC operations. Theoretical foundations, supported by empirical studies involving SC managers, can offer insights into pertinent key areas required to formulate strategic initiatives aimed at achieving desired business outcomes when implementing CAIT.

Although existing studies on human-AI collaboration have considered CAIT as a socio-technical system, empirical examination of this strategy as an intrinsic resource is limited. Intrinsic resources in the context of establishing and understanding the combinatorial factors of human-AI collaboration for successful business outcomes have not been acknowledged in extant literature (Przegalinska et al., 2025). Our research builds upon the RBV and STS to develop a model that examines the CAIT-SCWB and CAIT-SBP nexus as well as the mediating function of RAI. The choice of integrating two theoretical lenses is deemed necessary as it provides a holistic framework for addressing the technical, societal and organisational dimensions of SCWB and SBP. The aim is not to only theorise CAIT as a socio-technical system but also to develop unique insights about its impact (through RAI dimensions) on SCWB and SBP. Our theoretical model will help us understand what capabilities are required to strategies CAIT within organisations.

This study offers substantial contributions to Operations and Supply Chain Management (OSCM) research in several key areas. First, we use RBV and STS theories to answer the call on the importance of CAIT in solving SC-related challenges (Loske & Klumpp, 2021). Our study responds to the call by Mikalef et al. (2022), who advocate for practical approaches to the design and deployment of RAI. More specifically, we expand discussions around RAI design and use for SC outcomes from a holistic perspective. A summary of constructs and definitions is provided in Table 1.

3 Model development

The theoretical model developed in this study is rooted in the RBV and STS theoretical lenses. The hypothesised relationships are provided in Fig. 2 and discussed in detail below.

3.1 CAIT and SC outcomes (SCWB and SBP)

Proponents of CAIT advocate for the combination of human creativity, ethical judgement and contextual understanding with AI's computational power may significantly enhance business outcomes (Hermann and Huang, 2020). Defining CAIT from this perspective recognises the addition of a new resource and undergoing an internal redesign of operational processes (Saenz et al., 2020) which may affect team performance. From an RBV perspective, human capital (intuition, ethical judgement and insights) and AI analytical tools are considered

Table 1 Constructs and definitions of the conceptual research model

Construct	Role	Definition	Source (s)
Human-AI collaborative strategy (CAIT)	Independent variable	Human-AI collaborative strategies refer to the process of developing socio-technical systems in which human agents and AI systems collaborate in a mutually beneficial manner	Adapted from Kong et al. (2023)
AI accountability	First-order construct	AI accountability refers to the process of enabling the user to identify, interpret and evaluate the behaviour of an AI system	Adapted from Wieringa (2020)
AI fairness	First-order construct	AI fairness focuses on reducing unfair consequences, discrimination, and misjudgement of a specific user group using algorithms and data in operations. Non-discrimination forms the bedrock for AI fairness	Adapted from Memarian and Doleck (2023)
AI sustainability	First-order construct	AI sustainability refers to the integration of environmental, social, and individual factors into the development, design and interactions offered by an AI system	Adapted from Bjorlo et al. (2021)
Supply chain well-being (SCWB)	Outcome	Supply chain well-being (SCWB) is defined as the comprehensive approach to a SC's overall health. The emphasis is on the balance between operational excellence and the responsible treatment of all stakeholders	El-Baz and Ruel (2021); Gu et al. (2021); Queiroz et al. (2021a and 2021b); Wamba and Queiroz (2021); Wieland and Durach (2021); Vann Yaroson et al. (2024)
Sustainable business performance	Outcome	A holistic view of sustainability dimensions, including business, economic and environmental to facilitate business performance	Epstein and Roy (2003); Dey et al. (2020) and (2019); Saha et al. (2022); Vann Yaroson et al. (2024); Gupta et al. (2021)
Responsible AI (RAI)	Mediating variable	Responsible AI refers to the holistic approach of integrating ethical, moral and societal principles in the design and use of AI-related technologies	Second-order construct

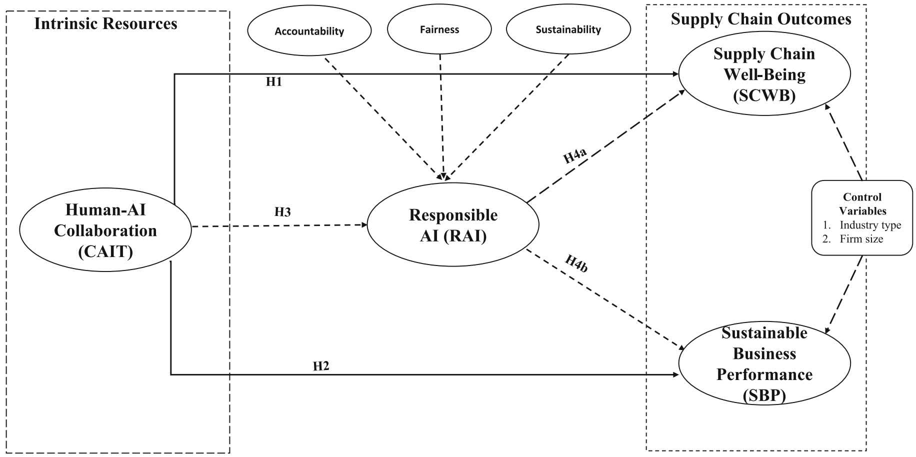

Fig. 2 The proposed research framework

critical resources for desired (Barney, 1991). Similarly, the ability to successfully combine and transform these resources to achieve the desired outcomes is rare. It implies that for CAIT, SC managers must possess the knowledge, skills and experience to effectively use AI technology that facilitates its integration with other SC operations (Davenport & Ronanki, 2018) and adapt to changes induced by AI technology.

Traditionally, the use of AI in SCs involves processing large quantities of real-time inventory-level data for accurate demand forecasting and strategic procurement (Toorajipour et al., 2021). Challenges may arise from the inability to successfully integrate human and AI systems due to misalignment of processes, boundary issues, organisational culture, lack of interoperable systems, and insufficient training and expertise (Loske & Klumpp, 2021). For example, in demand forecasting, Nair and Saenz (2024) argued that the degree of involvement of agents in CAIT differed by product characteristics. Where fast moving products with limited historical data may require higher human intuition than highly volatile products. Simon et al. (2024) showed that terms of interoperability including setting objectives, clarifying roles, negotiating responsibilities and coordinating mechanisms for effective collaboration were pertinent in CAIT. These highlights understanding boundary constraints, and the flexibility required for CAIT.

In SCWB, however, the focus differs. The scope transcends optimising processes to addressing ethical practices, improving workforce development and long-term stability. Thus, the intuition and ethical judgement of SC managers in these scenarios encompass social and ethical considerations that support informed decision-making (Charles et al., 2023). These in turn contribute to efficiency, cost reductions and value creation. Thus, our study contends that CAIT is an intrinsic resource necessary for organisations to achieve competitive advantage. These intrinsic resources include the skills, expertise, and capabilities of human agents interacting with AI systems. Similarly, the resources employed to develop CAITs contribute to building socio-technical capabilities for the design and deployment of RAI for successful business outcomes. In response, we argue that collaborative strategies that enhance human-AI interactions can overcome these challenges and improve business outcomes. Hence, we propose the hypothesis:

H1 *SCs that possess human-AI collaborative strategies and can effectively integrate them into business operations will achieve supply chain well-being.*

AI-powered technology capabilities have been documented to facilitate endeavours that contribute to the preservation of environmental resources, including low-carbon management (Roux et al., 2023); greener transport networks (Song et al., 2021); and weather forecasting (Cardil et al., 2019). Integrating human-AI dimensions into the decision-making regarding sustainability provides opportunities and insights that help firms improve sustainability practices (Kar et al., 2022). For instance, the actionable insights provided by AI may provide inspiration for innovative, sustainable business practices, including innovative products and services and business model innovation (Di Mattia et al. 2008). Actions towards attaining innovative business models may enhance employee skills and attitudes towards sustainability, which may in turn enhance sustainability performance. These successes are dependent on the successful design, deployment and integration of human agents and AI systems collaborative strategies. As such, AI system design must extend beyond analysing patterns and trends to understanding sustainability drives and goals within the framing of human intuitions and judgements. SC firms that adopt human-AI collaborative strategies and integrate them effectively into their operations can achieve long-term sustainable business performance. It highlights the importance of synergy between human intelligence and AI in the modern business environment.

H2 *SC firms that possess human-AI collaborative strategies and can effectively integrate them into business operations will achieve sustainable business performance.*

3.2 CAIT and RAI

RAI requires holistic integration (accountability, fairness and sustainability) in its design and implementation (Dignum, 2019). However, understanding the process involved remains inconclusive in the existing literature. Primarily, researchers highlight the need for transparency in all dimensions. AI accountability, for instance, is achieved through making algorithms accountable (Busuioc, 2020). Here, algorithmic transparency is believed to facilitate accountability as users and policymakers investigate the reasons behind AI decision-making. Wachter et al. (2017) and Busuioc (2020) demonstrated that AI accountability depends on the transparency of algorithmic models transmitted to users. Other studies argue that transparency in process development is critical (Vythilingam et al., 2022).

The contention is that AI system designers are responsible for creating accountable processes and that their transparency supports AI accountability. For instance, Vythilingam et al. (2022) showed that AI users' refusal to disclose personal information about past unethical behaviour and emotions to an AI system adversely affected the development process. Yet, some studies view AI transparency and accountability as interrelated factors (Ahmad et al., 2020; Sharma et al., 2022a), a source of trust (Shin, 2023) and demonstrate the convergence of the two concepts. Overall, hidden biases can undermine the accountability of AI interactions, and mitigating this issue requires transparency from humans and AI system design (Berscheid & Roewer-Despres, 2019).

Similarly, AI fairness as a dimension of RAI emphasises transparency as critical in deploying AI fairness (Claure et al., 2022) to address potential harm and discriminatory bias that may arise from human-AI collaboration. Zhang et al. (2020) highlighted the importance of policymakers in clearly defining users' social, normative, and legal boundaries through iterative and interactive processes for AI fairness. Other studies support human collaboration

(Ruf & Detyniecki, 2021). In this context, the authors argue that limiting AI fairness to computational and algorithmic issues is inadequate as it does not address the dialogue or trust between designers and machines (Saeed & Omlin, 2023). Therefore, AI fairness necessitates transparent user feedback through collaborative strategies for human-AI interactions. CAIT emphasises human-AI interaction through strategies that promote transparency, leading to a shared understanding of perceived fairness (McEneaney, 2013). We hypothesise that the deployment of AI fairness is influenced by the collaborative strategies of human-AI interactions.

AI sustainability depends on the ability of AI systems to integrate societal and environmental factors into their design and implementation. Additionally, it provides proactive guidance to consumers regarding sustainable efforts through AI interactions (Van Wynsberghe, 2021). These skills depend on the transparency of AI systems, as academics suggest that the absence of open and honest interactions among firms impedes the creation of sustainable AI (Osifo, 2023). Some studies argue that openness between AI systems and their users is essential for AI sustainability (Sanders et al., 2019). Encouraging the development of sustainable AI systems requires a link between a firm's governance transparency and the transparency of its AI systems (Al Shamsi et al., 2020). Others believe that ethics and transparency necessary for AI sustainability result from the joint effort of AI creators and users, necessitating long-term commitment and trust from human agents to AI systems (Bedué & Fritzsche, 2022; Khakurel et al., 2018). However, these claims have not been fully substantiated in the literature. Therefore, this study proposes that the use of collaborative approaches that enhance human-AI transparency can establish ethical principles that foster the development of more sustainable AI systems. Therefore, we argue that open and collaborative strategies that facilitate cooperation between humans and AI significantly influence the design and deployment of RAI systems.

H3 *Human-AI collaboration, when structured as a socio-technical system, statistically significantly enhances responsible AI outcomes.*

3.3 The mediating role of responsible AI (RAI)

Integrating accountability, fairness and sustainability elements of RAI in the design and deployment of AI systems has been suggested to address the associated AI challenges and thus enhance SC outcomes. AI accountability, for instance, through effective monitoring and auditing, leading to streamlined operations will ensure that AI systems adhere to regulatory standards, thereby avoiding legal complications and penalties (Mikalef et al., 2022). Non-discriminatory harm as a minimum standard of fairness (Leslie et al., 2019) addresses biases and facilitates secure procurement by ethically connecting and working with suppliers (Sanders et al., 2019; Wang et al., 2022). This approach mitigates discrimination or unfair impacts on their stakeholders and effectively establishes confidence between SC focal firms and their stakeholders, mitigates risks, and promotes sustainable business performance (Wu et al., 2024). It implies that AI fairness ensures non-discrimination in decisions related to stakeholder selection and permits a fair breakdown of stakeholders. Stakeholders who feel aggrieved by a failure to comply with this non-discriminatory principle could file lawsuits, which may economically penalise the organisation. Following Malesios et al. (2020) model, AI fairness is a sustainable practice that contributes to the SC outcomes.

RAI also focuses on the impact of AI systems on individuals and society from a more sustainable perspective (Sharma et al., 2022b). This is done to minimise any negative impact that supports and promotes the long-term welfare and goals of users (Larsson et al., 2021). In SC outcomes, AI-related systems have been used to enhance the speed, accuracy and efficiency in designing and sourcing sustainable products as well as adapting to customers' real-time needs (Sanders et al., 2019; Wamba et al., 2020; Hallikas et al., 2021; Saha et al., 2022). However, there is less focus on how AI systems can impact workers' health and safety, stability and survivability of SCs.

As such we contend that with RAI as a bridge between CAIT and SC outcomes, human-AI integration that adheres to human values, regulatory requirements, and ethical principles will be enhanced. RAI also enhances the impact of CAIT on SC outcomes by proactively building trust through transparent decision-making, facilitating explainability, increasing trust and enhancing collaborations. The mediating role of RAI may human agents to view AI collaborators as teammates and/or tools rather than as threats (Herrmann and Huang, 2020). RAI therefore bridges the gap between AI-powered technical capabilities and human-driven socio-organisational goals enabling SC outcomes. These connections, however, have not been extensively studied in the current OSCM literature.

H4a *Responsible AI (RAI) mediates the link between human-AI collaboration and supply chain well-being by fostering effective socio-technical system alignment.*

H4b *Responsible AI (RAI) mediates the link between human-AI collaboration and sustainable business performance by fostering effective socio-technical system alignment.*

4 Methodology

4.1 Instrument development and design

This study examined the contribution of CAIT in enhancing SCWB and SBP mediated by the holistic dimensions of RAI (fairness, accountability, and sustainability) using the RBV and STS theories. A cross-sectional survey-based instrument (questionnaire) was developed from the existing literature to identify the appropriate constructs and test the hypothesised model. The initial questionnaire was piloted among ten SC experts in the UK to assess the questionnaire's face validity, identify wording and formatting ambiguity, and determine if the constructs realistically reflected concerns in the industry about RAI (Saunders et al., 2019). Repetitive and unclear wordings were removed or changed, and new items were added. This was in line with experts' recommendations.

Respondents who completed the survey needed to be knowledgeable about the investigated phenomenon (Bryman et al., 2019). As such, respondents had to meet a set of recruitment criteria, including (1) frequency of technology use at work, (2) managerial capacity for decision-making within the UK's operations and supply chain management, and (3) awareness of AI systems and their implications for competitive advantage in SCs (see Sect. 4.2.). Purposive sampling, a non-probability sampling technique, was considered appropriate for determining the sample size (Saunders et al., 2019). This technique ensured that anyone identified as matching the recruitment criteria was invited to participate in the study using the Prolific (www.prolific.com) survey recruitment platform. The survey questionnaire was hosted on Qualtrics, a web-link survey. Ethics approval was obtained from the Toulouse Business School (TBS).

The scales for the various constructs were adopted from validated instruments in existing literature. Appendix A provides a summary of the scales used, their descriptive statistics and the supporting literature. Five constructs—collaborative AI (CAIT), fairness, accountability, sustainability, sustainable business performance (SBP), and supply chain well-being (SCWB)—were mobilised to test the hypothesised model. CAIT was measured using a four-item scale adapted from Kong et al. (2023). Responsible artificial intelligence (RAI) was measured as a Type II second-order construct (reflective first-order and formative second order). Type II second-order construct provides a framework for researchers to model abstract dimensions by specifying lower-order components (Hair et al., 2019). In this study, RAI is composed of three lower-order constructs (AI accountability, fairness and sustainability). The proposed model is consistent with the guidelines by Diamantopoulos and Winklhofer (2001). It implies that the first-order constructs are theoretically distinct and contribute to the second-order construct. A six-item scale measured SBP (Dey et al., 2020) and SCWB (Vann Yaroson et al., 2024). The items within each construct were measured using a five-point Likert scale, where 5 indicated "strongly agree" and 1 indicated "strongly disagree". A summary is provided in Table 1. Firm size (turnover) and industry type were used as control variables in this study. Industry types were controlled since they captured different conditions of the environment that may influence a SCs design and deployment of AI systems.

4.2 Data collection

The UK's SC was the empirical context of this research because of its AI advances and initiatives to accelerate AI adoption. The government AI Readiness Index (Oxford Insights, 2022) ranked the UK third out of 181 countries in AI adoption after the USA and Singapore. It was also imperative that the participants were directly engaged in AI implementation for SC strategies and had knowledge of the subject matter (Bryman et al., 2019). Each participant was expected to represent a focal firm and provide their perspective on the phenomenon being studied. The questionnaire was administered through a web-link survey sent via email to participants across several industries in the UK's SC. It included additional information on research intent, consent, and assurance of confidentiality.

We obtained 301 usable responses. The demographic characteristics indicated that over 50% of the respondents held either operations or production managerial roles and decision-making responsibilities. The size of the firms represented in the study varied from medium-sized firms (8.30%) to large corporations (61.8%). The majority of the respondents (57.8%) worked in the service industry, 10.3% in health/pharmaceuticals, 9.96% in manufacturing, 8.97% in retail and wholesale, 5.64% in construction/mining, 4.65% in transportation, and 2.66% in food. A summary of the information is provided in Table 2. We used Harman's single-factor test (Harman, 1976) and the Variance Inflation Factor (VIF) criteria (Kock, 2015) as suggested by Queiroz et al. (2021b) and Podsakoff et al. (2003) to look for a common method bias (CMB) and collinearity. The findings indicate the absence of CMB, as the cumulative average for Harman's test was 28.5% and the VIF values were below 4 (see Appendix B).

4.3 Data analysis and findings

Partial least squares structural equation modelling (PLS-SEM) was used to analyse the data. This was considered appropriate for our investigation based on the recommendations of Wolf et al. (2013) and Sideridis et al. (2014) due to the complex nature of our model, which required no prior assumptions. The study's goal was predictability, which PLS-SEM provides (Sarstedt et al., 2020). In addition, our statistical analysis demonstrated sampling adequacy,

Table 2 Demographic characteristics of responding firms

Profile	Sample (N = 301)	Percentage (%)
Gender		
Male	180	59.8
Female	120	39.8
Prefer not to say	1	0.03
Respondent's position		
Operations/production manager	153	50.8
Business strategist/executive	65	21.6
Other	42	13.9
Supply chain/logistics manager	41	13.6
Firm size (Annual Turnover M, £)		
< 20	25	8.3
20–50	21	6.97
50–150	21	6.97
151–250	11	3.65
251–400	18	5.98
401–600	19	6.31
> 600	186	61.8
Industry		
Services	174	57.8
Health/pharmaceuticals	31	10.3
Manufacturing	30	9.96
Retail/wholesale	27	8.97
Construction/mining	17	5.64
Transportation	14	4.65
Food	8	2.66

as a sample size of 250 (fewer than 301) was required to achieve the desired statistical power. A two-stage reflective formative approach was employed using a disjoint two-stage approach (Becker et al., 2012), where the first stage considers only the lower-order components and gets the later variable scores to form higher-order constructs (Sarstedt et al., 2020; Wetzels et al., 2009).

4.3.1 Reliability and validation of measurement scales

We established the reliability and validity of the first-order constructs using the outer loadings, Cronbach's alpha score, and composite reliability. All the values were above the recommended 0.60 threshold (Hair et al., 2019). The convergent validity of all the constructs was above the threshold of 0.60, indicating a good fit of the measurement variables used for the model. Discriminant validity was tested using Fornell and Larcker's (1981) criteria and confirmed using Hair et al.'s (2019) recommendation. This meant that the AVE's square root for the identified constructs was higher than the scores' square root. The results are presented in Table 3. The findings suggest that values exceeded the recommended 0.5 threshold, indicating that all the constructs were reliable and valid.

Second-order constructs were validated using weights of the outer loading and variance inflation factor (VIF). In line with recommendations by Hair et al., (2017), the findings show that VIF values are below 3 as presented in Table 4. The Normed Fit Index (NFI) value was

Table 3 Assessment of reliability, convergent and discriminant validity of reflective constructs

	(1)	(2)	(3)	(4)	(5)	(6)
(1) ACCT	n/a					
(2) CAIT	0.591	n/a				
(3) FAIR	0.627	0.735				
(4) SBP	0.456	0.392	0.461			
(5) SCWB	0.584	0.523	0.573	0.611		
(6) SUST	0.698	0.722	0.829	0.491	0.602	n/a
AVE	0.729	0.545	0.666	0.535	0.507	0.576
Cronbach alpha	0.630	0.722	0.835	0.781	0.804	0.816
Composite reliability	0.843	0.827	0.888	0.851	0.860	0.872

Table 4 Second-order construct validation

Constructs	Measures	Weight	VIF	R2	Q^2	Q^2predict
Human-AI collaboration (CAIT)	CAIT1	0.315	1.41			
	CAIT2	0.315	1.348			
	CAIT3	0.395	1.545			
	CAIT4	0.324	1.318			
Supply chain well-being (SCWB)	SCWB1	0.199	1.502	0.316	0.079	0.149
	SCWB2	0.259	1.807		0.095	
	SCWB3	0.246	1.519		0.101	
	SCWB4	0.225	1.401		0.052	
	SCWB5	0.245	1.835		0.073	
	SCWB6	0.226	1.675		0.05	
Sustainable business performance (SBP)	SBP1	0.218	1.68	0.198	0.026	0.067
	SBP2	0.316	2.021		0.025	
	SBP3	0.299	1.516		0.043	
	SBP5	0.28	1.384		0.036	
	SBP6	0.248	1.325		0.052	
Responsible AI (RAI)	ACCT	0.334	1.392	0.386	0.157	0.379
	FAIR	0.425	2.037		0.332	
	SUS	0.423	2.139		0.307	
Model fit (SRMR)	0.074					

0.725, following Bentler and Bonett's recommendations from 1980, and the SRMR was 0.07 (Hu & Bentler, 1999), indicating that further evaluations of the model's fit were adequate.

4.3.2 Structural model

We assessed the model's in-sample explanatory power using R^2 and its out-of-sample predictive relevance using RMSE and Q^2 (Sarstedt et al., 2020). The significance of estimates (t-values) is obtained by performing a bootstrap analysis with 10,000 replicates. The partial least squares method structural equation modelling (PLS: PLS-SEM) was used to test our theoretical framework and hypothesised relationships on SmartPLS. The structural paths and the associated coefficients of the model are shown in Fig. 3 and Table 5. Our analysis revealed a statistically insignificant effect between CAIT and SCWB (β = 0.096, t = 0.1454, p > 0.05) or SBP (β = 0.031, t = 0.411, p > 0.05). Additionally, the link between RAI, supply chain well-being (β = 0.480, t = 8.164, p > 0.05), and sustainability (β = 0.474, t = 7.622, p >

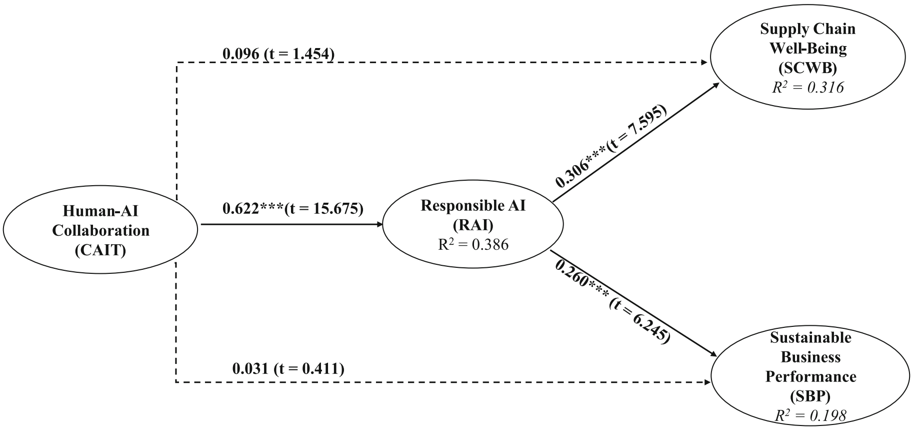

Fig. 3 Estimated relationships of structural model. Note: ***$p < 0.001$, **$p < 0.01$, *$p < 0.05$

Table 5 Hypothesis testing of structural paths

Hypothesis	Structural paths	β	T statistics	*P* values	Outcome
H1	CAIT—> SCWB	0.096	1.454	0.146	Not supported
H2	CAIT—> SBP	0.031	0.411	0.681	Not supported
H3	CAIT—> RAI	0.622	15.675	0.000***	Supported
H4a	RAI—> SBP	0.419	6.592	0.000***	Supported
H4b	RAI—> SCWB	0.492	8.662	0.000***	Supported
Control	Firm size—> SCWB	– 0.044	0.987	0.324	Not supported
Control	Firm size—> SBP	0.047	0.875	0.382	Not supported
Control	Industry—> SCWB	0.073	1.54	0.124	Not supported
Control	Industry—> SBP	0.012	0.202	0.84	Not supported

CAIT = human-AI collaboration, RAI = Responsible AI, SCWB = supply chain well-being, SBP = sustainable business performance, p < .01**

0.05) is positive and statistically significant. The effect size (F^2) was also examined to decide the effect size. F^2 allows us to evaluate the contribution of an exogenous construct to the R^2 of an endogenous latent variable. We also examined the influence of control variables on SCWB and SBP. The results showed that the effect on firm size and industry type were insignificant on the two outcomes.

4.3.3 Test for mediation

To examine the mediating role of responsible AI (RAI) on SCWB and SBP, a bootstrapping approach is used (Preacher & Hayes, 2008). We used the parameter estimates from the bootstrapping process in PLS on a resampling of 10,000 subsamples to calculate the standard error of each mediating effect. The mediation path ratio was then calculated by dividing the indirect effect by the total effect. In line with the recommendations by Sarstedt et al. (2019), we first confirm the mediated paths (CAIT → RAI → SCWB and CAIT → RAI → SBP) are significant by first including the direct paths (CAIT → SCWB and CAIT → SBP) in the model. Our analysed data showed that both supply chain well-being ($\beta = 0.096$, $t = 0$, $p > 0.05$) and sustainable business performance ($\beta = 0.031$, $t = 0.411$, $p > 0.05$) were non-significant, indicating full mediation. Confidence intervals greater than zero provided further justification for our mediation analysis. In Table 6, the outcomes of the meditation analysis are associated with H4a and H4b.

4.3.4 Predictive validity

The model was also assessed using the Q^2 predictive validity to establish the relevance of the exogenous variables (Woodside, 2013). Q^2 prediction is used to verify how well the observed values are reproduced by the model and its estimated parameters (Chin, 1998). To imply the predictive relevance of the hypothesised structural model, Q^2 values are expected to be greater than 0 (Hair et al., 2019). The analysed data showed that responsible AI ($Q^2 = 0.379$), supply chain well-being ($Q^2 = 0.149$), and sustainable business performance ($Q^2 = 0.067$) have values greater than 0, depicting satisfactory predictive relevance. The model fit was examined using the test of composite-based standardised root mean square residual (SRMR). As presented in Table 4, the SRMR value of 0.074, which is below the 0.08 threshold, confirms the overall fit of the PLS path model (Henseler et al., 2016).

5 Discussion and implications

5.1 Discussion

Although there is growing interest in human-AI collaboration in SC operations, the conditions under which these can be integrated to achieve desired business outcomes are still largely underexplored in empirical literature. Our analysed data offer striking results, which contrast the vast amount of literature advocating for the transformative power of human agents and AI systems. This may be largely due to the absence of empirical evidence grounded in a theoretical framework (Simon et al., 2024). Existing studies also note that human-AI collaboration transcends the technical tasks to include the design, deployment and the successful symbiotic relationship of human agents and AI systems. Interestingly in a survey by Secondmind (2024), managers cited distrust and interoperability as major inhibitors when

Table 6 Mediation analysis

Effect	Structural path	β	*T* value	Ratio to total effect (%)	Bias corrected 97.5% confidence interval	Outcome
Direct	CAIT—> SCWB	0.096	1.454	23.8	[−0.037–0.219]	Full mediation (Hypothesis 4a supported)
Indirect	CAIT—> RAI—> SCWB	0.306	7.595***	76.1	[0.229–0.385]	
Total effect	CAIT—> SCWB	0.402				
Direct	CAIT—> SBP	0.031	0.411	10.6	[−0.118–0.180]	Full mediation (Hypothesis 4b supported)
Indirect	CAIT—> RAI—> SBP	0.260	6.245***	89	[0.176–0.340]	
Total effect	CAIT—> SBP	0.292				

employing human-AI collaborative strategies to achieve desired business outcomes. Similar findings were noted by Simon et al. (2024) who showed the importance of interoperability, mutual learning and trust interacting over time to develop CAIT. Even though we are now aware that the technical knowledge and AI systems are not sufficient to facilitate SC-wide desired business outcomes, these remain largely underexplored, particularly SCWB and SBP.

Building on these identified theoretical gaps in the literature, the objective of this study was to understand whether human-AI collaboration could lead to the desired business outcomes of supply chain well-being and sustainability and if responsible AI intervened in the relationship. To address these questions, the notion of human-AI collaboration was conceptualised as an intrinsic resource that firms need to integrate and align with their business processes to achieve desired outcomes. We grounded the human-AI collaborative strategy in the RBV and socio-technical systems (STS) lens to emphasise the non-technical resources to be considered in its design and deployment.

Our analysed data, however, found an insignificant link between CAIT and business outcomes (SCWB, SBP). The findings highlight that the deployment of strategies to facilitate human-AI collaboration must extend beyond basic analysis patterns and trends in managing supply networks (demand forecasting, supplier selections, inventory management, risk management) and sustainability performance. It requires first identifying SC and sustainability drivers and goals for designing AI systems that meet these requirements. Human-AI collaboration in these scenarios is not one-size-fits-all (Nair & Saenz, 2024) but requires flexibility, following a reiterative process of designing and realignment. For instance, in SCWB where the emphasis is on the balance between operational excellence and the responsible treatment of all stakeholders (Vann Yaroson et al., 2024), human-AI collaboration may fail if AI systems have been designed to achieve standardised SC goals. While these findings contrast existing studies (Kar et al., 2022), they open up the debate on the forms of strategies that SC and sustainability-driven firms require to achieve human-AI synergy for successful outcomes.

The significant mediation of RAI in the link between CAIT, SCWB and SBP reinforces the alignment and reiterative process in the design and deployment of human-AI collaboration strategies. SCWB and SBP goals require understanding the dynamic nature of human elements. Consequently, RAI ensures that human-AI integration adheres to human values, regulatory requirements, and ethical principles (Mikalef & Gupta, 2021). It delivers transparency and accountability, helping humans understand and trust decisions made by AI. RAI therefore bridges the gap between AI-powered technical capabilities and human-driven socio-organisational goals enabling supply chain well-being and sustainability.

By proactively building trust through transparent decision-making, RAI facilitates trust by holding AI systems accountable to ethical and sustainability standards.

5.2 Theoretical implications

Our findings have several theoretical implications. For instance, the desired SC outcomes of human-AI collaboration to date have focused on logistics (Loske & Klumpp, 2021); demand forecasting (Nair & Saenz, 2024) and retail operations (Revilla et al., 2023). There is limited evidence of a holistic approach to SC operations where cognisance is given to humans in the loop. We address this shortcoming by providing empirical support for the framing of human-AI collaborative strategies and the resulting business outcomes (SCWB and SBP) through RAI, by analysing data from 301 SC executive-level managers. Through our narrative and research model, CAIT is described as an intrinsic resource within a socio-technical system designed to enhance SCWB and SBP through the integration of RAI dimensions. Hence, SCs that focus their efforts on designing and deploying CAIT can use it to drive strategy and inform the decision-making processes of top management. Investment in CAIT with considerations for RAI can facilitate the speedy generation of insights, create real-time monitoring of SC activities and identify operational inefficiencies.

Secondly, the absence of a significantly direct link between CAIT, SCWB and SBP may suggest the narrow focus of CAIT. It may infer the need to vary human-AI collaborative design across firms, SCs, product categories and the various dimensions of SCWB and SBP. Our analysis aligns with some studies which imply that CAIT strategies cannot be boxed into a single category -one-size-fits-all-and that the responsibility of the agents (human-AI) may vary depending on the SC goal, product characteristics and/or data type (Nair & Saenz, 2024). This identifies CAIT as a flexible and social-technical system that needs to be aligned with organisational goals to achieve a desired business outcome.

In addition, the impact of CAIT on both SCWB and SBP is found to be fully mediated by RAI indicating that RAI can fundamentally alter the way SCs employ human-AI collaborations. Given that there will always be a gap between human intuition and AI models, embedding RAI dimensions will facilitate the modelling of the minds (Vossing et al., 2022), which will lead to the nurturing of trust (Simon et al., 2024), mitigate information asymmetry and improve transparency. It also highlights the importance of organisational culture and learning in human-AI collaboration, as upskilling and reskilling of managers will require embedding shared values and assumptions of AI use. The findings align with Kong et al. (2023), who found that human-AI collaboration, especially among employees, enhanced their skills and judgements.

Through our analysis, we developed a framework for human-AI collaboration establishing boundaries which hitherto were elusive in existing literature. Figure 4 illustrates the boundaries and decision-making distribution between human and AI-powered systems in human-AI

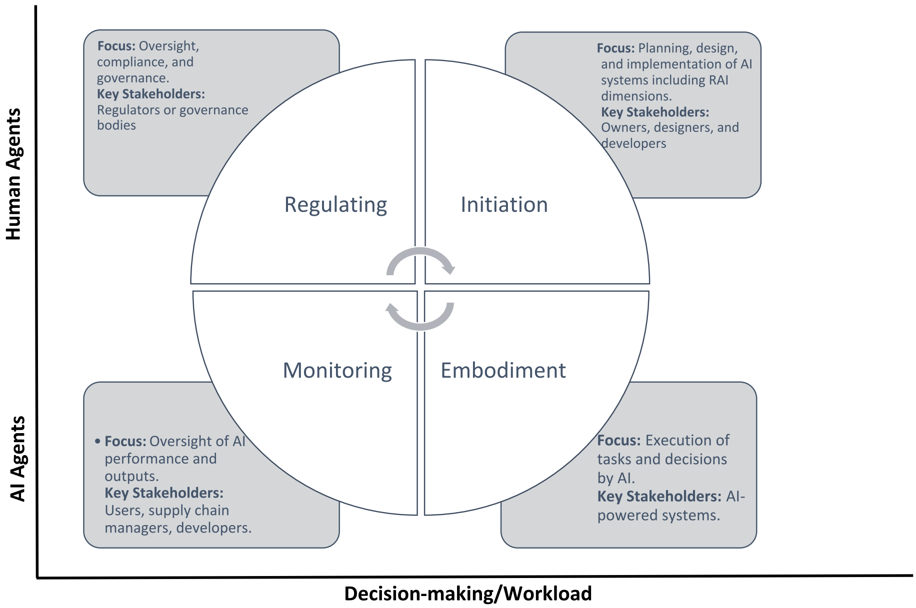

Fig. 4 A Framework for human-AI collaboration for supply chains

collaboration to achieve business value in SCs It shows the distinct phases of an operational cycle where the vertical axis indicates the degree to which tasks or roles are handled by human agents or AI systems. Human agents are emphasised in the upper half of the framework while AI agents are in the lower half. On the horizontal axis, the decision and /or workload in the human-AI collaborative strategies are presented where more human involvement is on the left while those relying on AI are on the right. The regulating quadrant involves tasks relating to oversight, and compliance which are typically regulators and governing authorities and require high human involvement and less reliance on AI for decision-making. In the initiation quadrant (top right), task setting and designing of AI systems requires input from owners, designers and developers. Human agents at this stage are responsible for establishing goals and frameworks for AI operations. Introducing RAI dimensions and organisation goals is usually in this quadrant. The monitoring (bottom right) quadrant involves overseeing AI systems and their output, ensuring that performance aligns with expectations. Human agents here including users, supply chain managers and developers are responsible for verifying and interpreting AI results to ensure compliance. The embodiment quadrant requires that tasks are fully automated, and decisions are supported by AI-powered systems. AI manages routine tasks and human involvement is minimal. Even though the quadrants are distinct, the framework is a cyclical process, showing feedback or iterative refinement between these phases.

Finally, by comprehensively examining the characteristics of accountability, fairness, and sustainability in RAI, our research is among the first to offer evidence of its significance in human-AI collaboration. Particularly, on how enhanced human-AI collaborative strategies augment RAI systems. This is warranted as intrinsic organisational collaboration techniques promote sociotechnical interactions between human agents and AI, leading to an integrated strategy for RAI systems. A positive and significant link between CAIT and RAI indicates that human-AI interactions are essential to the development of RAI. The accountability component enhances transparency in decision-making, fairness emphasises the necessity for inclusivity and reduces discriminatory outcomes (Saeed & Omlin, 2023), and sustainability underscores the importance of communication among stakeholders. The affirmative correlation between CAIT and RAI underscores the necessity for constructive discourse among stakeholders. Simon et al. (2024) assert that effective dialogue should not solely focus on rectifying AI system deficiencies but also improve users' decision-making processes by utilising quality interactions and recognising unconscious biases. This effect could enhance a SC's reputation and strengthen long-term partnerships among stakeholders, addressing the societal dimensions of SBP (Kamble et al. 2020; Sharma et al., 2020).

5.3 Practical implications

Our analysed data offer several implications for practitioners. First, this study shows that human-AI collaboration transcends investment in another trending emerging technology and/or humans and AI working together. Complementing those mentioned above, our results demonstrate that efficiently harnessing the associated dividends of human-AI collaborative strategy requires recruiting employees with good technical and managerial skills across all levels of SC operations, embedding AI use in the decision-making process to build trust and fostering an organisational culture of learning to facilitate the integration processes. This reframes AI from being merely a tool to becoming an integral team member in SC operations. Thus, CAIT requires the combined effects of these intrinsic resources and strategically aligning these resources with organisational goals to achieve desirable business outcomes. It therefore implies that human-AI collaboration requires actioning several processes, with top management commitment and a clear plan for SC-wide adoption of AI use and deployment.

Secondly, existing studies have already highlighted the importance of all these factors in human-AI collaboration and offering managers guidelines in its design and implementation (Chowdhury et al., 2022a; Simon et al., 2024). One of the most elusive elements is achieving the right boundary between human intuition and AI capabilities devoid of discrimination and ethical bias to foster trust. With several studies now reporting the importance of trust and responsibility in AI system use (Omrani et al., 2022), embedding responsibility in human-AI collaboration is critical to achieving business goals. It also requires an interactive process where AI systems learn from humans which in turn feedback in a loop as presented in Fig. 4.

In essence, responsible AI culture rests on the idea that priority be accorded to AI systems that enable, transparency, fairness and accountability. As an emerging area of interest among managers, responsible AI systems will require internal organisation redesign, including skilling and reskilling managers who collaborate with AI systems for decision-making. Thus, achieving interoperability will require complementarities of both agents (human and AI), focus on data requirements and the anticipation of organisational constraints. This will facilitate the establishment of boundaries for AI use when blended with human intuition. SC firms that can successfully integrate these resources to achieve seamless human-AI integration forge a stronger connection with SCWB and SBP. To achieve this, however, top management needs to demonstrate the strategic symbiotic relationship between humans and AI systems. Here emphasis is on the importance of stakeholder relationships within the RAI ecosystem, including designers, users, regulators, and AI systems.

Core resources and protocols needed to develop these strategic relationships need to be outlined to help managers construct assessment tools to benchmark their strengths and weaknesses. The main pillars that constitute RAI systems can help identify weak points and intrinsic resources in the design and deployment of human-AI collaborative strategies prioritised for better integration. Policymakers and managers should prioritise these protocols to ensure ethical AI use. Additionally, developers must encourage active user participation to address ethical concerns comprehensively and avoid bias (Richey et al., 2023).

Given that SC firms are still at the nascent stage of their human-AI collaborative strategy, it is pertinent to have a good overview of the requirements and associated costs. Additionally, while it may be easy to acquire some resources, such as AI systems and even human skills, other resources, such as seamless integration, interoperability, trust, responsible AI culture and understanding the demarcation between AI systems and human judgement, require careful planning and well-documented processes across stakeholders and the entire supply chain.

Further, our analysed data show that even by fostering strong human-AI collaborative strategies, supply chain well-being and sustainability are not directly achieved. It implies that although SCs may be able to establish human-AI interactions, further action is required for desired outcomes to materialise. Human-AI collaborative strategy is only an element of a SC's ability to generate intrinsic resources, and harnessing its benefits involves designing and aligning these strategies to SC goals. It is not one size fits all and requires flexibility, agility and SC capabilities. Managers need to realise that the human-AI collaboration strategy is only one element of the system; the other is responsiveness, which requires alignment with business goals.

Finally, we highlight the need for SC managers to prioritise AI interoperability for RAI system performance, especially given SCWB's and SBP's multifaceted nature. Identifying and optimising the components of the human-AI collaborative ecosystem is crucial. As illustrated in our framework, this ecosystem involves interconnected roles among stakeholders, forming a virtuous cycle where transparency drives efficiency. By adopting these collaborative strategies, SC managers can ensure continuous human-AI interaction, aligning RAI systems with the sustainability goals of Industry 5.0 (European Commission, 2021). This approach not only promotes individual organizational transparency but also generates broader ecosystem benefits.

6 Conclusions, limitations, and areas for further research

This study evaluated the impact of CAIT in enhancing SBP and SCWB. More specifically, the moderating role of RAI from a holistic perspective was analysed to include accountability, fairness, and sustainability. A theoretical framework using the RBV and STS perspectives was developed and tested on a sample of 301 SC managers in the UK. The empirical analysis identified CAIT as an intrinsic resource necessary for SC firms to build and design RAI systems. Similarly, the socio-technical interactions that produce RAI systems moderate the link between CAIT, SBP, and SCWB. The findings suggest that while AI-powered technologies can address SC challenges, several conditions may be required. These include designing collaborative AI strategies for human-AI interactions as an organisational intrinsic resource. Human-AI interactions are socio-technical interactions. Consequently, CAIT is an essential organisational resource for designing and implementing RAI in a way that effectively addresses SC problems. Our research contributes to the SC literature by highlighting the benefits of using AI-powered technologies through collaborative human-AI strategies and the mediating effect of designing and deploying RAI systems holistically.

Like any other study, this research has several limitations that should be considered as avenues for future research. First, while the study focused on SC managers across several industries in the UK, some sectors were more heavily represented than others, which may have skewed the results. Future studies should focus on a single industry for more detailed insight, as the applicability of AI technologies varies among sectors.

Second, the human-AI interactions at the heart of the CAIT are particularly complex. Our study reveals a multitude of actors involved in CAIT's development, from designer to user, from expert to layman. Moreover, these interactions are multi-level, from the simple human-AI level to the higher team-system level. Future research is necessary to gain a better understanding of these various levels of interaction, their dynamics, and the main obstacles, especially if human–machine interactions are particularly complex and multi-level in the context of CAIT and, more broadly, RAI.

Third, while our study views CAIT as a socio-technical and unique resource, specific to each organisation, our model focuses only on its consequences, not its antecedents. Future research could focus on its antecedents, i.e., the organisational factors necessary for its development, to enhance sustainable performance. Future research should focus on developing governance frameworks and strategies dedicated to CAIT and, more broadly, RAI.

Finally, given the scale of AI development in all organisational activities and its role as a decision-making tool, this study may bring implications beyond SC and information systems research to support RAI's development using CAIT. CAIT could also serve as a fundamental concept for enhancing various aspects of sustainable performance, including innovation, human resources development, recruitment activities, and automated financial decision-making.

Appendix A: Outer loading for first-order construct

	ACC	CAIT	FAIR	Firm size	SBP	SCWB	SUST	Industry
ACC1	0.836							
ACC2	0.727							
ACC5	0.664							
CAIT1		0.733						
CAIT2		0.699						
CAIT3		0.810						
CAIT4		0.707						
FAIR2			0.847					
FAIR3			0.751					
FAIR4			0.810					
FAIR5			0.852					
Firm size				1.000				
SBP1					0.693			
SBP2					0.797			
SBP3					0.729			
SBP4					0.644			
SBP5					0.720			
SBP6					0.630			
SCD1						0.631		
SCD2						0.763		
SCD3						0.725		
SCD4						0.653		
SCD5						0.769		
SCD6						0.722		
SUS1							0.729	
SUS2							0.705	
SUS3							0.760	
SUS4							0.814	
SUS5							0.783	
Industry								1.000

Appendix B: Descriptive statistics of measurements

Items	Standardised loading	Mean	SD	t-values
ACCT1	0.839	0.839	0.021	39.076
ACCT2	0.736	0.733	0.044	16.647
ACCT5	0.666	0.663	0.051	13.184
CAIT1	0.734	0.734	0.035	21.235
CAIT2	0.702	0.699	0.04	17.623
CAIT3	0.811	0.811	0.023	35.662
CAIT4	0.711	0.708	0.04	17.635
FAIR2	0.848	0.848	0.018	46.811
FAIR3	0.754	0.752	0.034	21.908
FAIR4	0.812	0.811	0.028	29.107
FAIR5	0.853	0.853	0.018	46.566
SBP1	0.705	0.704	0.041	17.391
SBP2	0.804	0.803	0.024	33.065
SBP3	0.724	0.722	0.039	18.595
SBP4	0.649	0.648	0.047	13.841
SBP5	0.725	0.724	0.035	20.491
SBP	0.625	0.624	0.051	12.273
SCWB1	0.632	0.631	0.053	11.944
SCWB2	0.767	0.767	0.03	25.287
SCWB3	0.734	0.733	0.035	21.057
SCWB4	0.66	0.658	0.046	14.388
SCWB5	0.771	0.771	0.027	28.323
SCWB6	0.734	0.734	0.035	21.236
SUST1	0.733	0.731	0.039	18.858
SUST2	0.708	0.707	0.039	18.021
SUST3	0.764	0.763	0.035	21.847
SUST4	0.817	0.817	0.021	38.233
SUST5	0.785	0.784	0.034	23.307

Appendix C: Path coefficient

	Path coefficients	Alpha 1%, power 80%	Alpha 5%, power 80%	Alpha 1%, power 90%	Alpha 5%, power 90%
ACC—> SBP	0.177	323	199	418	275
ACC—> SCWB	0.126	631	389	819	539
CAIT—> ACC	0.491	42	26	55	36
CAIT—> FAIR	0.584	30	19	39	26
CAIT—> SUST	0.561	32	20	42	28
FAIR—> SBP	0.17	348	214	451	297
FAIR—> SCWB	0.235	182	112	235	155
Firm size—> SBP	0.044	5155	3176	6686	4399
Firm size—> SCWB	- 0.044	5196	3201	6739	4434
SUST—> SBP	0.186	290	179	376	248
SUST—> SCWB	0.252	159	98	206	136
Industry—> SBP	0.024	17,881	11,016	23,192	15,258
Industry—> SCWB	0.078	1656	1020	2148	1413

Appendix D: Fornell-larcker criterion for LOC

	ACC	CAIT	FAIR	Firm size	SBP	SCWB	SUST	Industry
ACC	0.746							
CAIT	0.491	0.739						
FAIR	0.56	0.584	0.816					
Firm size	0.147	− 0.004	0.037	1				
SBP	0.389	0.293	0.4	0.083	0.704			
SCWB	0.403	0.4	0.478	− 0.01	0.528	0.712		
SUST	0.587	0.561	0.701	0.048	0.412	0.491	0.759	
Industry	0.048	− 0.003	− 0.043	− 0.074	0.027	0.084	0.029	1

Appendix E: Control variables

Control	Supply chain well-being			Sustainable business performance		
	Weight	*t* value	Sign	Weight	*t* value	Sign
Firm size	− 0.05	1.104	0.269	0.045	0.839	0.401
Industry type	0.071	1.475	0.14	0.011	0.196	0.844

Data availability The data that support the findings of this study may be available from the corresponding author upon reasonable request. The data are not publicly available due to [restrictions—containing information that could compromise the privacy of research participants].

Declarations

Conflict of interest Emilia Vann Yaroson declares no conflicts of interest. Amelie Abadie declares no conflicts of interest. Melanie Roux declares no conflicts of interest.

Ethical approval All procedures (online survey) involving human participants were in accordance with the ethical standards of Toulouse Business School (TBS) and with the 1964 Helsinki Declaration and its later amendments or comparable ethical standards.

Informed consent Informed consent was obtained from all individual participants included in the study at the pre-screening stage of the survey.

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