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The interplay of data-driven insights and AI anxiety in shaping the impact of AI capabilities on circular economy capability

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ABSTRACT

In a world facing pressing environmental challenges like climate change and resource scarcity, Artificial Intelligence (AI) is widely regarded as a powerful tool to enhance and support sustainability goals via Circular Economy Capability (CEC). The organizational capacity to leverage this technology, Artificial Intelligence Capability (AIC), is conceptualized through the lens of the Resource-Based Theory (RBT) as the capacity to effectively implement and utilize AI to generate strategic value. However, the direct relationship between AIC and CEC is not straightforward. The purpose of this research is to investigate this nuanced relationship by examining how socio-technical factors such as Data-Driven Insights (DDI)—actionable inferences derived from analytics over data—and AI Anxiety—stemming from employees' fear of job loss—shape the relationship between AIC and CEC. Using a moderated mediation model and Partial Least Squares Structural Equation Modeling (PLS-SEM), we analyzed data from firms with moderate to high technology maturity. While the study's results are primarily based on context-specific evidence, which invites further investigation into generalizability to other settings, our findings suggest that the direct effect of AIC on CEC is not significant. Instead, DDI significantly mediate the relationship, confirming that AIC must be bundled with actionable insights to create value. Crucially, AI anxiety negatively moderates the effect of DDI on CEC. This means that while organizations may generate valuable insights, employee resistance and fear hinder their effective translation into sustainability practices. This study highlights the critical socio-technical barriers to AI adoption and their impact on achieving sustainability goals.

1. Introduction

In a world grappling with climate change, soil degradation, and water pollution, the rapid advancement of digital technologies is considered crucial for sustainability in general [34] and, more specifically, the United Nations' Sustainable Development Goals (SDGs), which comprise a set of global goals aimed at creating a prosperous and peaceful world by addressing major challenges like poverty, inequality, climate change, and environmental degradation [39]. In particular, Industry 4.0 technologies like Artificial Intelligence (AI) are deemed instrumental in contributing significantly to sustainability across various domains and toward meeting sustainability goals [7].

The potential to revolutionize the way industries engage with circular economy practices is particularly evident when AI technologies are integrated into organizational processes [91]. These positive links arise because AI enables organizations to optimize resource use and orchestrate activities, such as reuse, remanufacturing, and reverse-logistics decisions, thereby fostering resilience and innovation [6]. Artificial

Abbreviations: AI, artificial intelligence; AIC, artificial intelligence capability; ANDI, *asociación nacional de empresarios de Colombia* (national business association of Colombia); AVE, average variance extracted; BCG, Boston consulting group; BDA, big data analytics; CEC, circular economy capability; GRI, global reporting initiative; HTMT, heterotrait-monotrait; PLS-SEM, partial least squares structural equation modeling; PLS, partial least squares method; RBT, resource-based theory; SDGs, sustainability development goals; SEM, structural equation modeling; SMEs, small and medium-sized enterprises; UNDP, United Nations development programme.

Data Availability

The datasets generated and/or analyzed during the current study are available from the corresponding author upon request.

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Intelligence Capability (AIC) is conceptualized as the ability to implement and utilize AI effectively [66]. In turn, Circular Economy Capability (CEC) is the organizational ability to effectively implement practices that optimize resource use, reduce waste, and promote material circulation [94]. Although AIC is arguably a driver of CEC [11], the relationship between AIC and CEC is more nuanced than previously suggested, as it is confronted with both technical and human-related barriers to AI adoption [71], including technological, financial, and regulatory obstacles [86], along with psychological aspects that include cognitive load and employee well-being [24].

First, scholars have focused on addressing technical barriers to AI adoption by emphasizing organizational challenges [77], like the difficulty of identifying and prioritizing barriers to adoption [65], economic constraints [49], technological interoperability issues and a lack of robust infrastructure [17]. Previous research established that barriers to AI adoption are largely technical and systemic, demonstrating that internal deficiencies such as pervasive technical skills gaps —with Kumar et al. [55] reporting that 73.3 % of surveyed organizations cited this deficit, alongside 50.0 % reporting data management challenges—and external friction from a lack of necessary stakeholder awareness among clients and the public (P [54]) impede effective implementation. These findings define the initial research scope by focusing on tangible, objective hurdles, such as skills and organizational readiness, thereby highlighting the need to understand deep-seated psychological resistance, like AI anxiety. However, the adoption of AI poses additional challenges, particularly in the context of circular economy practices [87], as existing digital technologies alone have shown limitations in achieving long-term sustainability [76].

According to the Resource-Based Theory (RBT), competitive advantage arises through the bundling of both tangible and intangible resources [70]. It then implies that AIC alone are insufficient and must be combined with additional resources—such as Data-Driven Insights—to create the necessary capabilities for circular economy practices [10]. Data-driven insights (DDI) are actionable inferences derived from analytics over internal and external data [34]. These inferences enable organizations to transform AI-generated data into actionable knowledge, thus optimizing resource use, predicting outcomes, and improving sustainability [37], with data analysis being crucial for enhancing innovation [95] and achieving environmental and financial sustainability in production [36]. These insights connect AIC to CEC by reducing operational and strategic uncertainty. Within an RBT lens, data (with proper governance) are resources, while AIC are capabilities that convert those resources into insights; insights then enable CEC by orchestrating reuse, remanufacturing, and reverse-logistics decisions [67]. However, despite its importance, the role of DDI as a bridge between AIC and CEC remains underexplored in the literature. Hence further examination is needed to understand how AI can effectively support sustainability goals.

Second, the area of human-related challenges, has been largely underexplored as most existing research focuses on technical skills gaps (S [55]) and stakeholder awareness issues (P [54]) as barriers to AI adoption, while far fewer studies have delved into the psychological impacts of AI on employees, such as the fear of job loss and issues related to cognitive overload, stress, and reduced autonomy [24]. Importantly, AI anxiety, the fear that AI will replace human jobs [92] can hinder the effective realization of AI's potential by generating employee resistance. A 2024 report by the Boston Consulting Group revealed that 49 % of U.S. employees fear job loss due to AI, triggering AI anxiety [13]. This psychological barrier may reduce the effective adoption of AI-driven solutions, limiting the benefits that DDI could provide to enhance CEC, highlighting the necessity to address human impacts to fully realize the advantages of digital transformation [24].

These socio-technical challenges highlight that while AI has the potential to increase efficiency and enable CEC [37], DDI may play a significant role that deserves further academic scholarly. Indeed, although Ghasemaghaei and Calic [37] examined the impact of insights on overall organizational outcomes, the specific role of different levels of DDI in AI-driven circular economy transformations needs to be fully understood. Similarly, there is limited knowledge on how AI anxiety may hinder organizations' ability to fully leverage AI in developing CEC. These gaps may impede progress toward achieving the Sustainable Development Goals (SDGs). Thus, the relationship between AIC and CEC is far from straightforward, calling for a more nuanced understanding.

Hence, the purpose of this paper is to investigate the nuanced relationship between AIC and CEC, emphasizing the mediating role of DDI in this relationship. The study also explores the moderating role of AI anxiety in the generation and application of these insights by organizations. While previous research has linked AI capabilities to various forms of organizational innovation, including circular economy performance [10], adoption of sustainable practices [11], supply chain innovation [87], and product success [93], little attention has been paid to the role of DDI in making firms more sustainable. Moreover, the moderating effect of AI anxiety in this process remains poorly understood. Hence, this research integrates and synthesizes the literature on AIC, AI Anxiety, and CEC to propose a theoretical model that illustrates how the interplay between human (AI Anxiety) and technical factors (DDI) influences the effect of AI Capability on CEC.

Beyond the general promise of AI for circularity, the feasibility of circular economy strategies hinges on robust data and information flows across the product lifecycle. Prior work shows how engineering data models and interoperability standards enable the flow and reuse of data across design, production, and operations [80]. Complementarily, Acerbi et al. [1] identify the data and information requirements that firms must satisfy to enact circular strategies at scale. We build on these premises to argue that AIC translate into CEC through DDI.

By addressing these dynamics, this research contributes to the ongoing conversation about the socio-technical implications of AI in pursuing sustainability goals, which ultimately contribute to the Sustainable Development Goals (SDGs). Provided that, Industry 4.0 technologies like Artificial Intelligence (AI) contribute significantly to sustainability across various domains [7], and such technologies have become instrumental resources for competitiveness [67] and sustainability [17], we take a RBT approach, as it helps understand how organizations recombine resources in unique ways to develop distinctive capabilities. Specifically, we posit that DDI are strategic, tangible resources that firm may leverage to foster their CEC. The value of DDI comes from their enabling power, acting as a mediator of the relationship between AIC and CEC.

The research process begins in Section 2 by performing a comprehensive literature review, which synthesizes the Resource-Based Theory (RBT) with socio-technical factors to conceptually build and hypothesize our moderated mediation model. This model specifies the expected relationships between AI Capability, Data-Driven Insights, AI Anxiety, and Circular Economy Capability. Section 3 then details the methodology, including the collection of empirical data via a structured survey and the application of Partial Least Squares Structural Equation Modeling (PLS-SEM) for analysis. Section 4 presents the results of the statistical analysis, interpreting the derived coefficients to assess the support for each hypothesis. These results should be interpreted with caution due to the context-specific nature of the evidence from a single country (Colombia) and the small sample size, which prevents us from disentangling industry effects. Finally, Section 5 discusses the theoretical and practical implications of our findings, addresses the study's limitations, and outlines directions for future research, including the need to test whether these findings hold in broader contexts.

2. Theoretical background and hypotheses development

Resource-Based Theory (RBT) provides a framework to study how organizations combine resources and build capabilities that drive competitive advantage. This theory posits that a firm's long-term success is contingent upon resources that are valuable, rare, inimitable, and non-substitutable [11]. Using this framework, we argue that AIC, when paired with DDI, can be considered key resources that foster the development of CEC.

The value of data is realized not in its raw form but when it is integrated with complementary assets to create unique, hard-to-imitate capabilities that improve resource optimization, reduce waste, and advance sustainability practices [10], also contributing to efficient production [36], and improved innovation [95]. The concept of capabilities is a core tenet of RBT, which posits that a firm's sustained competitive advantage stems from resources that are valuable, rare, inimitable, and non-substitutable [12]. The combination of data with other resources creates a unique bundle that competitors cannot easily replicate or acquire [75]. Furthermore, a firm's ability to effectively deploy and combine these assets, particularly in a manner that is difficult for rivals to imitate, constitutes a critical capability [4]. In a rapidly changing environment, a firm's capacity to dynamically integrate and reconfigure its data and complementary assets to maintain relevance and advantage is essential for long-term success [88].

In our context, we contend that DDI are both tangible and intangible resources. Raw data may be widely available and proprietary, making them storable, accumulable, and re-deployable assets with specificity to the firm's processes and customers; their informativeness and asset specificity increase with curation, lineage, and interoperability [57]. While this view implies that data are tangible (data, technology, and financial resources), crucially, advantage emerges when data are transformed into insights and enacted through human and intangible components (technical/managerial skills, data-driven culture, and organizational learning) that strengthen dynamic capabilities [67]. In other words, high-quality, fine-grained, and longitudinal datasets can be valuable, rare, imperfectly imitable, and non-substitutable, and thus, a source of competitive advantage, following the RBT [1].

The previous reasoning also implies that AIC help optimize decision-making and resource management [81]. However, the effectiveness of AIC also depends on the organization's ability to convert AI-generated data into actionable insights. These DDI—descriptive, predictive, and prescriptive—help firms diagnose inefficiencies, predict material and energy flows, and simulate optimal strategies for circularity [37]. According to RBT, the bundling of AIC and DDI transforms resources into strategic assets that provide long-term competitive advantage [66]. These insights are context-specific and path-dependent, which makes them difficult for competitors to replicate, thereby providing a sustainable advantage in the market through mechanisms like self-sovereign data spaces that ensure control over data and models [76]. For instance, organizations can integrate AIC into business processes by leveraging interconnected Industry 4.0 technologies for greater efficiency [69] and innovation [91] and thus optimize supply chains and improve circular economy practices [23].

The complexity and specialization required to develop and leverage these insights render AIC particularly difficult to replicate, positioning them as key drivers not only of competitive advantage [8] but also of CEC, especially in increasingly complex manufacturing systems where advanced ITs are crucial for holistic sustainability [17].

However, psychological factors such as AI Anxiety—the fear of job displacement due to AI—represents a socio-technical barrier to fully realizing AI's potential in fostering circular economy practices as it leads to employee resistance, limiting the generation of data-driven insights and hindering decision-making processes [59], exacerbated by challenges such as cognitive load, stress, and fear of job loss associated with new technologies [24]. This psychological barrier creates a gap between AI implementation and its potential to support CEC. By combining AIC and Data-Driven Insights while addressing AI Anxiety, organizations can better integrate circular economy strategies into their operations, aligning sustainability goals and competitive advantage.

As illustrated in Fig. 1, our proposed model suggests a relationship between AIC and CEC, mediated by DDI and moderated by AI Anxiety. In the following sections, we elaborate on these relationships and present the hypotheses based on the interaction between technical and human factors.

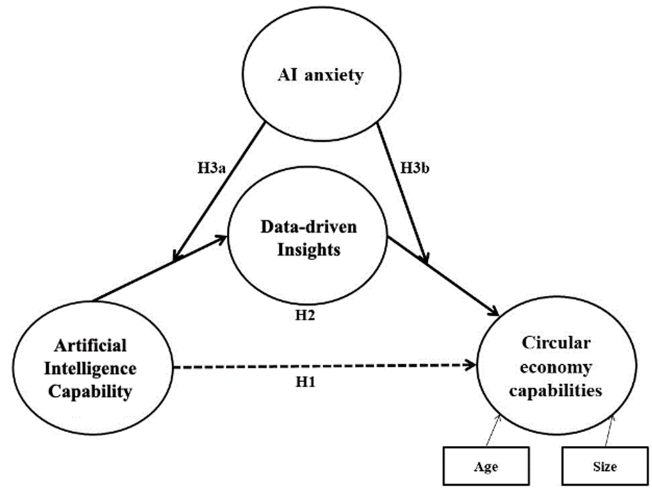

Fig. 1. Conceptual model.
Source: authors.

3. The direct influence of AIC on CEC

AIC are pivotal in enabling organizations to optimize resource use, minimize waste, and promote material reuse and recycling, thus enhancing CEC. AI-powered analysis of large datasets enables the prediction of product lifecycles, facilitating interventions such as recycling or remanufacturing and optimizing material usage to minimize waste [23], leveraging predictive capabilities to optimize resource allocation and reduce waste through simulations [36].

Organizations can facilitate decision-making that supports circular economy strategies by transforming raw data into actionable insights through the integration of AI and Big Data analytics, enabling smarter and more predictive decisions in dynamic environments [6]. AIC also helps maximize the value of resources across their lifecycle, which drives sustainable innovation and favors waste reduction, which drives sustainable innovation and favors waste reduction by supporting engineering design and optimizing processes throughout a product's lifespan [17]. Furthermore, AI enables the seamless integration of circular economy practices into organizational operations, aligning sustainability goals with operational efficiency [10].

Recent research demonstrates that companies with advanced Big Data and AI analytics capabilities are better equipped to implement circular economy strategies, leveraging robust data analysis and predictive capabilities to improve productivity [7] and innovation [95]. Indeed, these technologies enhance supply chain flexibility and improve sustainable performance by enabling data-driven decision-making (Edwin [32]). Additionally, AI enhances coordination across the value chain, essential for optimizing material reuse and recycling within circular economy models [42], by improving interoperability and enabling seamless information exchange across organizations [6].

AI-enhanced CEC is then an expected outcome. Despite encountering numerous barriers to adopting circular economy practices, AIC assist organizations in mitigating some of these barriers. This mitigation is achieved primarily through the enhanced predictability and operational optimization afforded by AI. By providing predictive insights, AI reduces the financial uncertainty and risk associated with high upfront investments, while simultaneously reducing costs through improved machine maintenance and production efficiency [89]. Furthermore, AI minimizes operational disruptions by utilizing DDI to orchestrate complex circular activities, such as reuse, remanufacturing, and intricate reverse-logistics decisions, thereby facilitating a managed transition away from traditional linear models [53].

AI Capabilities (AIC) enhance Circular Economy Capability (CEC) through four complementary mechanisms: first, lifecycle traceability—Internet of Things sensorization plus interoperable engineering data standards such as AutomationML expose material and product lineage across design, production, use, and end-of-life, enabling recall, reuse, remanufacturing, and closed-loop logistics [8]. Second, ML-based predictive maintenance reduces unplanned downtime and extends asset lifetimes, directly lengthening use cycles and reducing scrap, as documented by recent systematic reviews in manufacturing contexts [15]. Third, data-driven forecasting improves the predictability of demand for remanufactured products and the timing/quantities of returns, which informs reverse-flow planning, inventory positioning, and component harvesting [90]. Finally, ML-augmented optimization supports collection routing, disassembly sequencing, and refurbish-versus-recycle decisions under uncertainty, improving cost-to-recover and service levels in circular loops [16].

Consequently, we propose the following hypothesis:

H1: Artificial intelligence capabilities (AIC) positively influence Circular Economy capability (CEC).

4. The mediating role of data-driven insights in the relationship between AIC and CEC

AI technologies can facilitate the transition to circular economy (CE) practices by transforming CE principles into actionable business strategies [22]. AI enables firms to analyze the efficiency and sustainability of their production processes, support decision-making through simulations and forecasts, and ultimately optimize resource use [50], leveraging autonomous data analysis to improve efficiency and reduce costs for financial and environmental sustainability [36]. However, the effective deployment of these capabilities is contingent upon tangible resources, including data and technological infrastructure [10].

Implementing CE requires interoperable, life-cycle–spanning data. Engineering standards such as *AutomationML* illustrate how data can flow and be reused across heterogeneous tools and phases, reducing information discontinuities that block circular practices [80]. However, beyond AI infrastructure and technical capabilities, organizations must cultivate managerial skills to interpret and apply these DDI effectively [84]. Complementing this view, prior work identifies the specific data and information categories needed for circular manufacturing, e.g., product composition, usage profiles, degradation and failure modes, and end-of-life pathways, showing that insufficient data quality and accessibility are primary barriers [1]. In our framework, AIC addresses these frictions by generating DDI that leverage interoperable, high-fidelity data to support CE decisions.

DDI, the creation of new knowledge that enhances a firm's problem-solving capacity, are a critical outcome of this process [37]. These DDI occur in three forms (descriptive, predictive, and prescriptive) each providing a comprehensive informational context for informed decision-making [95] and being crucial in enabling CEC [37].

Descriptive insights elucidate the current and historical state of production systems, rendering inefficiencies in sustainability practices more salient [45]. Implemented through dashboards and related visualization tools, these insights support rigorous diagnosis of sustainability performance and the strengthening of circular-economy capabilities (CEC).

Predictive insights forecast outcomes, such as energy consumption, demand, or product-lifecycle impacts, by leveraging historical data and statistical/ML models to anticipate the effects of altering specific variables [22], thereby enhancing both material resilience and eco-efficiency [52]. As AI capabilities (AIC) intensify, firms improve the tracking of material and energy flows [27] and the accuracy of demand forecasting [31], thereby optimizing resource utilization across operations [36].

Prescriptive insights employ simulation and optimization to test alternative decisions ex ante and estimate their impacts on circular-economy strategies, thus recommending actionable courses of action that support target outcomes [82]. The ensuing iterate-evaluate-learn cycle cultivates organizational learning and capability building, further reinforcing CEC [37].

Such analyses—describing, predicting, and prescribing—correspond to the three levels of Data Analytics, as conceptualized by Darbanian et al. [26], with the predictive level being the most salient in recent research. These levels account for growing complexity and sophistication, indicating that a firm could simultaneously perform descriptive and prescriptive analyses only if it has mastered descriptive techniques. This means the firm has achieved the highest maturity in data analytics [28]. Additionally, every level of analysis might have differential effects on a firm's performance.

These insights serve as a bridge to transform AI-processed raw data into actionable knowledge that guides firms in optimizing resource use and achieving sustainability [89], enabling real-time analysis [76], information sharing, and collaborative decision-making through advanced digital tools and platforms [6]. Consequently, it is plausible to propose that DDI mediate the relationship between AIC and CEC.

Indeed, previous research reveals significant effects of descriptive and predictive insights on exploration and exploitation, while prescriptive insights appear to exert a lesser impact [37]. Considering that exploration and exploitation processes lead to organizational learning [61], and learning is key to capability development [35] that enhances organizational performance [33], we hypothesize that more advanced AIC leads to enhanced DDI, which in turn improve circular economy decision-making. In this connection, Johnson et al. [47] found that insights improve innovation competences. Therefore, as firms learn from analyzing data, they also enhance their learning capabilities, which may assist in developing other capabilities, such as CEC.

Hence, our second hypothesis is as follows:

H2: AI capabilities (AIC) increase circular-economy capabilities (CEC) through data-driven insights.

5. The moderating role of AI anxiety

It is generally assumed among researchers and practitioners that AI provides significant advantages to organizations. However, implementing a new technology is complex and, thus, challenging. AI implementation faces three types of barriers [19]: access, cognition, and behavior, which can be categorized more broadly into technological, financial, regulatory, and psychological obstacles [24]. Although the literature predominantly focuses on access, some researchers have pointed to the need to explore cognitive and behavioral factors influencing the effective use of ICTs [14]. Investigating psychological aspects is relevant since access *per se* does not guarantee the full realization of technology benefits; cognitive and behavioral barriers might be a significant factor in explaining the delay in AI adoption and, thus, prevent organizations from generating useful insights.

Regarding psychological barriers, previous research has addressed the impact of AI implementation on employees' attitudes in their workplace, indicating that employees' attitudes toward adopting AI are two-folded: while they might acknowledge the benefits, they can also harbor negative attitudes [59], such as cognitive overload, stress, and fear of job displacement [24]. For instance, while people are reluctant to take AI-generated phone calls, they may feel confident about having their digital assistants perform certain tasks [59]. Similarly, Brougham and Haar [18] find that when employees realize that their employers are exploring new technologies, they tend to feel undervalued and unappreciated. Bellini et al. [14] explored the interaction between self-efficacy and anxiety during the first stage of mandatory ICT implementation and discovered that anxiety levels reveal the extent to which individuals are hesitant about using ICTs. This work posits that the level of self-efficacy correlates with anxiety, creating cognitive limitations that hinder ICT implementation. Thus, while some employees might perceive this technology advancement as an opportunity to increase their efficiency, others are more reluctant and even frightened by the possibility of losing their jobs [59]. This paradoxical situation might lead to AI anxiety. Additionally, La Torre et al. [56] have emphasized the importance of addressing factors such as technology acceptance, technology self-efficacy, and source credibility to reduce employees' resistance to machine-based decision-making, which calls for training programs and supportive work environments to promote employee well-being and adaptability [24].

According to Mikkelsen et al. [68], "technology anxiety" is defined as an employee's unpleasant experience using a specific technology. This anxiety manifests through employees' emotional responses towards technology in the form of uneasiness, frustration, apprehension, and fear. These negative feelings might emerge when employees become more aware that AI facilitates their interactions with robots to perform certain tasks more efficiently [83] but, at the same time, has the potential to make them redundant [25], thus causing psychological disorders, including anxiety [9]. Furthermore, automation by AI can generate turnout intention and depression [18], as the changing nature of work and the introduction of new roles can lead to increased psychological strain for employees [24]. It could also lead to a higher perception of job insecurity, especially amid an authoritarian organizational culture [60]. Interestingly, this anxiety can also affect managers' readiness to adopt these technologies. These results indicate that AI anxiety is a common occurrence among both managers and employees, which increases the likelihood of resistance to technology implementation within the organization. They also imply that the human factor, regardless of hierarchical position, remains a key factor in fully leveraging AI for decision-making.

Besides fearing the loss of their jobs, employees may also distrust technology. For example, Niszczota and Conway [72] show that laypeople tend to perceive the usage of AI for research purposes as less morally acceptable than delegating certain tasks to doctoral students. AI adoption might prompt employees to question the value of their contributions, as in the case of a Chinese hospitality company, where employees expressed concerns about their commitment to their jobs and their sense of belonging to the workplace and suspected that technology would make them redundant upon realizing that the company was planning to implement more AI; as a consequence, they experienced higher adverse effects on turnover intentions [58].

While AIC are generally assumed to lead to improvements in CEC, we hypothesize that this relationship is mediated by the organization's ability to generate DDI. However, when AI anxiety is present, organizations may fail to fully capitalize on the insights provided by AI or may generate fewer insights overall. This diminished ability to leverage descriptive, predictive, and prescriptive insights, as outlined by [37], ultimately limits the development of CEC, highlighting the importance of addressing AI anxiety to realize the full potential of AIC. Hence, our next hypothesis is as follows:

H3a: Mediation in the path between AIC and DDI will be reduced when there is AI Anxiety.

AI adoption induces organizational turmoil as organizations must adapt their processes to increasingly rely on these new technologies [66]. Barriers to AI adoption include a lack of knowledge regarding digital technologies, employees' fear and lack of stakeholder awareness (P [54]). Nevertheless, greater awareness of AI's potential may also induce anxiety, slow AI adoption, thus preventing organizations from fully leveraging DDI. Employees' fear of job loss has been shown to delay AI implementation, triggering resistance to data usage in decision-making [19]. Moreover, some research points out that awareness can also lead to reservations about the use of AI, which raises the question of its impact on CEC development.

Research suggests that AI anxiety provokes resistance among both employees and managers, limiting the full adoption of AI technology [9]. A conflict emerges from AI anxiety: while individuals recognize that AI improves efficiency and accuracy, they fear it may ultimately make them redundant, leading to job loss. This mixed sentiment impairs the interaction between humans and AI, as employees may limit their use of AI outputs—such as descriptive insights—by withholding critical data or resisting the full integration of AI into their work.

In conclusion, AI anxiety triggers negative attitudes that can result in suboptimal AI implementation, affecting the development of CEC and the realization of sustainability goals. These psychological barriers reduce the effectiveness of DDI and hinder the positive outcomes typically associated with AI adoption [59], as failure to address human factors can prevent organizations from fully realizing the benefits of digital transformation [24]. That is, the process of describing and diagnosing material flows, energy consumption, or waste generation in complex production systems is more challenging when relying on human capacities exclusively in the absence of full AI technology implementation. Similarly, the ability to simulate or predict the results of intended adjustments regarding energy and material consumption and reuse is diminished when performed without the assistance of advanced AI technologies, or it can be weakened when employees provide incomplete inputs to train AI models, particularly when there is a lack of standardized metadata or common information models for effective machine learning model sharing [76]. Finally, descriptive insights may be disregarded when the suggested scenarios do not align with the organization's existing practices ("non-invented-here" syndrome). If the human part of this dyad does not trust or feels insecure, hesitant, or reluctant [9], it is less likely that DDI are fully tapped. Thus, the following hypothesis is proposed:

H3b: Mediation in the path between DDI and CEC will be reduced when there is AI Anxiety.

In view of the above, we have proposed a moderated mediation model, as shown in Fig. 1.

6. Methods

6.1. Sample and data collection

The proposed model (Fig. 1) was tested on a sample of manufacturing and service companies (Eurostat, 2009) from Colombia (Table 1), a country experiencing rapid growth in the adoption of AI applications [64]. Colombia is among the Latin American countries making the largest investments in the adoption of new digital technologies, including artificial intelligence [30]. Furthermore, the country has made strides in integrating circular economy principles into its industrial sectors through its National Circular Economy Strategy and is positioned as a key player in the circular economy transition in the region by setting ambitious goals for increasing the country's recycling rate and promoting sustainable business models [5]. In terms of sustainability, Colombia ranks 74th globally, with a score of 70.30 in the Sustainable Development Report 2024 [78]. Furthermore, the country leads SDG reporting in Latin America, with over 670 businesses registered on the SDG Corporate Tracker, a platform developed through collaborations between the government and the *United Nations Development Programme* (UNDP) for tracking corporate contributions to the SDGs and guiding policy decisions [40].

The fieldwork was conducted between January and May 2024 by sending an electronic questionnaire to executives from two separate databases of Colombian companies. The first database is commercially available and provided by a firm specializing in offering this type of service to higher education institutions. The second database consists of companies registered with the country's Chambers of Commerce. These databases collectively contain over 100,000 records, representing the same number of companies. Therefore, the first step involved identifying those companies belonging to sectors with high or medium digitization [20,62] and for which the contact information of the legal representative (senior executive) was available. After data cleaning, nearly 15,000 companies remained, and the questionnaire was sent to the corresponding number of email addresses. In the end, 298 responses were obtained, of which 197 were valid.

Table 1
Sample characteristics.

Sector	Activity	Frequency	%
Services	Telecommunications	22	11 %
	Financial and insurance activities	17	9 %
	Information service activities and computer programming	16	8 %
	Wholesale and retail trade	16	8 %
	Education	12	6 %
	Legal and accounting activities	8	4 %
	Architectural and engineering activities	6	3 %
	Human health	5	3 %
	Arts, entertainment and recreation	5	3 %
	Advertising and market research	4	2 %
	Other knowledge-intensive services	19	10 %
	Other less knowledge-intensive service	8	4 %
Manufacturing	Manufacture of wearing apparel	18	9 %
	Manufacture of food products	7	4 %
	Manufacture of chemicals and chemical products	6	3 %
	Manufacture of wood and of products of wood	6	3 %
	Manufacture of electronic products	4	2 %
	Manufacture of machinery and equipment	4	2 %
	Other manufacturing sectors	14	7 %
Size (Number of employees)			
Large (≥ 250)		146	74%
SMEs (≥ 10 - < 250).		51	26%
Respondent's position			
Presidency or General Management		46	23%
Human resources		36	18%
Systems and Technology		36	18%
Research and Development		21	11%
Finances		24	12%
Marketing		12	6 %
Production and Operations		22	11%

Source: authors.

This study applied the minimum R-squared method to determine the minimum sample size required to achieve a statistical power of 80 %, ensuring the test's ability to detect a significant path coefficient ($P < 0.05$) [41]. The total of 197 valid responses that were collected provided sufficient statistical power [51], exceeding 80 % [43]. Of these, 74 % are considered large companies (see Table 1).

6.2. Measurement scales

For this work, we adapted previously validated scales in literature, as described next:

AI capability. We used the tangible dimension of the scale developed by Mikalef and Gupta [66]. This scale was validated by Almheiri et al. [2] and used by Ameen et al. [3], who evaluate how AIC, when coupled with strategic ability improves product and service creativity.

Circular Economy Capability. We employed the scale devised by Zeng et al. [94], which has been used in Bag et al.'s [11] work on the external determinants of CEC, and by Martínez-Falcó et al. [63] on their study of the role of CEC on sustainable performance. We specifically considered the items applicable to manufacturing and service companies

Data-Driven Insights. We follow Ghasemaghaei & Calic's [37] approach to measure DDI. Previous research, including Gnizy [38] who explores how small data and big data interact to create insights, and Zhou and Zou's [97] exploration of how digital human resources practices influence the generation of DDI.

AI Anxiety. The scale proposed by Wang and Wang [92], which we use in the present study was previously employed by Kaya et al. [48] when studying the role of personality traits and other factors on employee attitudes toward AI.

Redundant or ambiguous items were eliminated prior to pretesting. Revisions addressed unclear terms, double-barreled statements, and context-specific jargon, yielding a final, reader-friendly instrument. All scales followed a Likert scale structure, with values ranging from 1 (strongly disagree) to 5 (strongly agree). Prior to the main survey, we administered a pretest ($n = 30$) to verify routing, timing, and clarity; minor wording changes were implemented accordingly.

Appendix A contains a detailed breakdown of each construct, including the original academic source, and the specific survey questions used in our data collection.

6.3. Reliability and validity

The reliability and validity of the measurement model were assessed using structural equation modeling (SEM) through the partial least squares (PLS) method [44]. To test our theory, we used Structural Equation Modeling (SEM), specifically the Partial Least Squares (PLS) approach, which is ideal for confirming complex relationships and building new theory [43,79]. At its core, SEM allows us to examine several cause-and-effect predictions at the same time, treating constructs like AIC and CEC as underlying factors measured by our survey questions. Our model is designed to test a moderated mediation, which offers a much richer understanding than a simple direct link. This involves two key concepts:

Mediation (The 'How'): This tests how one variable affects another indirectly. We propose that AIC influences CEC, but only by first creating Data-Driven Insights (DDI). We test whether the DDI variable acts as a critical bridge, or mediator, to confirm the process through which the technical capacity (AIC) delivers circular economy performance (CEC).

Moderation (The 'When'): This tests when a relationship is stronger or weaker. We investigate how AI Anxiety changes the strength of the DDI-CEC link. With this procedure we attempt to identify a crucial boundary condition—a human barrier—that either amplifies or dampens the organization's ability to turn insights into actual circular economy practices.

By evaluating the significance of the coefficients for these specific pathways, the SEM analysis confirms the process and boundary conditions under which AI adoption successfully translates into enhanced sustainability outcomes.

This approach was chosen for its capacity to estimate complex models involving numerous constructs, indicator variables, and structural paths in a straightforward manner. PLS-SEM is a causal-predictive technique that helps explain the relationships in statistical models by focusing on prediction [41,79]. To ensure the quality of our measurement model, we adhered to widely accepted criteria for reliability and validity. The thresholds for factor loadings (set at 0.7 or higher), Cronbach's alpha (CA) and composite reliability (ρ_A and ρ_C, set at 0.7 or higher), and the Average Variance Extracted (AVE, set at 0.5 or higher) serve a specific purpose. High factor loadings confirm indicator reliability, ensuring each survey item strongly measures its intended construct. Reliability scores (CA and composite reliability) confirm internal consistency, verifying that all items belonging to a construct are highly correlated and reliably measure the same concept. Finally, the AVE threshold confirms convergent validity, demonstrating that a construct accounts for more variance in its indicators than measurement error [43]. Results in Table 2 confirm the reliability and convergent validity of our model's constructs and items.

6.4. Discriminant validity

To confirm discriminant validity, it was verified that all Heterotrait-

Table 2
Reliability and validity.

Constructs	Loadings	CA	rho_A	rho_C	AVE
AI Capability		0.94	0.95	0.95	0.80
AIC1	0.91				
AIC2	0.93				
AIC3	0.93				
AIC4	0.92				
AIC5	0.76				
Circular Economy Capability		0.71	0.79	0.83	0.63
CEC1	0.87				
CEC2	0.86				
CEC3	0.61				
Data-Driven Insights		0.78	0.78	0.90	0.82
Prescriptive insights					
Dat1	0.90				
Dat2	0.91				
Predictive insight					
Dat3	0.85				
Dat4	0.83				
Dat5	0.80				
Descriptive insight					
Dat6	0.90				
Dat7	0.90				
Dat8	0.74				
AI Anxiety		0.91	0.93	0.92	0.53
AIAnx1	0.63				
AIAnx2	0.75				
AIAnx3	0.76				
AIAnx4	0.64				
AIAnx5	0.69				
AIAnx6	0.74				
AIAnx7	0.67				
AIAnx8	0.76				
AIAnx9	0.75				
AIAnx10	0.80				
AIAnx11	0.78				

*$p < 0.001$.
Source: authors.
Note: See Appendix A for descriptions of the items and their corresponding questions.

Monotrait (HTMT) correlation values remained below the established threshold of 0.85 ([21]a), as shown in Table 3.

6.5. Moderated mediation test procedure

Moderated mediation refers to the indirect effect of X (AI capability) on Y (Circular economy capability) through M (DDI), which varies depending on changes in W (AI anxiety) [46]. A two-stage PLS-SEM approach was followed to test this model: assessing direct effects in the first stage and the moderated mediation effect in the second. We calculated 95 % confidence intervals and the t-values of the coefficients of the different paths from a bootstrapping of 10,000 subsamples [21,79]. Mediation exists if the path from AI capability to DDI and the path from DDI to CEC are both statistically significant [73,96]. The f^2 value was also estimated to determine the effect size of the moderated mediation relative to the direct effect of AI capability on CEC. This value can be classified as low (0.02), medium (0.15), or high (0.35) [43].

Table 3
Discriminant validity.

Constructs	Heterotrait-Monotrait correlations			
	1	2	3	4
1. AI Capability				
2. Circular Economy Capability	0.10			
3. Data-Driven Insights	0.23	0.15		
4. AI Anxiety	0.28	0.37	0.19	

Source: authors.

7. Results

Table 4 displays the results of our estimations. While statistically robust, these results should be considered suggestive given that our sample size did not allow for validation across larger and more diverse contexts to ensure their generalizability. As can be observed from the direct model, the effect of AI capability on CEC is not significant. Therefore, H1 is not supported. In contrast, the indirect effects between AI capability and DDI, as well as between the latter construct and CEC, are both significant and positive in the moderated mediation model, thereby supporting H2. Regarding the effect of AI anxiety on mediation, the results indicate a negative and significant moderation only in the path between DDI and CEC. Therefore, H3a is not supported, but H3b is. In addition, the f^2 value of 0.20 indicates that the size of the moderated mediation is at an intermediate point between the medium (0.15) and high (0.35) values. These results are examined in detail below.

7.1. Relationship between artificial intelligence capabilities (AIC) and circular economy capability (CEC)

The results indicate that the direct effect of AIC on CEC is not

Table 4
Structural equation results.

Models	Paths	Coefficients	Confidence intervals at 95 %	Conclusions
Direct	Direct Effects			
	H1. AI capability → Circular economy capability ($R^2 = 0.02$)	0.10	[−0.24; 0.24]	Not supported
	Controls			
	Age → Circular economy capability	−0.06	[−0.19; 0.16]	
	Size → Circular economy capability	0.07	[−0.21; 0.21]	
Moderated mediation	Direct Effects			
	AI capability → Circular economy capability	0.04	[−0.10; 0.16]	
	AI capability → DDI	0.16**	[0.01; 0.27]	
	DDI → Circular economy capability	0.16**	[0.01; 0.30]	
	Indirect Effects			
	H2. AI capability → DDI → Circular economy capability	0.02*	[0.00; 0.04]	Supported
	Interaction Effects			
	H3a. AI anxiety x AI capability → DDI	0.06	[−0.08; 0.21]	Not supported
	H3b. AI anxiety x DDI → Circular economy capability ($R^2 = 0.18$; $f^2 = 0.20$)	−0.14*	[−0.25; −0.01]	Supported
	Controls			
	Age → Circular economy capability	−0.10*	[−0.23; 0.02]	
	Size → Circular economy capability	−0.01	[−0.13; 0.13]	

*$p < 0.05$; **$p < 0.01$; ***$p < 0.001$.
Source: authors.

significant ($\beta = 0.10$, $p > 0.05$), which leads to the rejection of H1.

7.2. The mediating role of DDI

The moderated mediation model supports H2, as the indirect effects between AI capability and DDI, as well as between DDI and CEC, are both significant and positive ($\beta = 0.16$, $p < 0.01$).

7.3. The moderating role of AI anxiety

The findings suggest that the relationship between AIC and DDI is not moderated by AI anxiety ($\beta = 0.06$, $p > 0.05$), leading to the rejection of H3a.

Simultaneously, our results show that AI anxiety significantly moderates the relationship between DDI and CEC ($\beta = -0.14$, $p < 0.05$), thereby supporting H3b.

8. Discussion

Building on the empirical results reported above, this study highlights the critical role of socio-technical factors in understanding the relationship between AIC and CEC. This section interprets the theoretical meaning of the findings, articulates their implications for scholarship and practice, and outlines limitations and avenues for future research.

8.1. Theoretical implications

8.1.1. Relationship between AIC and CEC

Our H1 predicted a positive relationship between AIC and CEC, relying on previous studies that have often highlight AI as a key enabler of CEC [11]. However, the non-significant direct effect of AIC on CEC questions the widespread assumption that the mere possession of advanced AI infrastructures automatically leads to sustainable outcomes.

This finding advances the RBT by emphasizing that resources such as AIC are potential rather than actual sources of competitive advantage. Their value is conditional upon complementary mechanisms that transform technological assets into capabilities [29]. In this way, our study refines the RBT by highlighting that digital resources require conversion mechanisms—in this case, DDI—to create value [89]. Theoretically, this implies that future extensions of the RBT should explicitly consider conversion efficiency as a determinant of whether technological resources yield sustainability-oriented capabilities.

8.1.2. The mediating role of DDI

For H2, we proposed and found support for DDI as a mediating variable in the relationship between AIC and CEC. Our findings confirm that DDI serve as a critical bridge between technical resources and circular capabilities. Previous research suggests that Big Data and AI-driven insights improve organizational innovation [10] and decision-making [37], yet it has not been empirically demonstrated how this process specifically supports the development of CEC. Our results extend the literature by proposing DDI as a resource integrator that translate the potential of AIC into sustainability outcomes. In particular, the descriptive, predictive, and prescriptive insights generated by AI assist organizations in optimizing resource use, reducing waste, and promoting circularity by diagnosing inefficiencies, forecasting outcomes, and simulating sustainability strategies [22]. Therefore, the theoretical contribution of H2 lies in proposing DDI as strategic conversion capabilities that operationalize the transition from technological capacity to sustainable performance.

8.1.3. The moderating role of AI anxiety

We hypothesized that AI Anxiety would negatively moderate both the link between AIC and DDI (H3a) and the DDI-CEC relationship (H3b). Contrary to expectations, we do not find support for H3a, that is, for the notion that AI Anxiety impacts the extent to which AIC generate DDI. By contrast, AI anxiety weakens the impact of DDI on CEC, supporting H3b.

This suggested partial moderation provides a nuanced theoretical insight into the socio-technical contingencies of AI-driven sustainability. The rejection of H3a shows that AI anxiety does not interfere in the generation of insights, suggesting that initial stages of AI deployment are perceived as efficiency-oriented rather than as job-threatening [59]. Conversely, the support for H3b reveals that AI anxiety negatively affects the application of insights, acting as a human-induced friction that limits the transformation of knowledge into circular practices [9]. These results add a behavioral layer to the RBT: even when firms possess valuable and rare resources (AIC, DDI), the effectiveness of these resources is reduced when socio-psychological conditions are unfavorable [74]. Thus, AI anxiety can be conceptualized as a negative intangible resource or frictional moderator that constrains the resource–capability conversion process. This contributes to the socio-technical literature by integrating psychological barriers into the understanding of how digital resources are enacted within organizations.

In summary, while previous research largely focused on the technical aspects of AI implementation [11], our findings challenge the assumption that AIC directly translates into improved CEC. By emphasizing the mediating role of DDI (descriptive, predictive, and prescriptive), our research bridges a gap in the literature, offering a more nuanced understanding of how AI, when combined with insights, becomes a resource capable of driving sustainability outcomes. This integrative perspective extends the Resource-Based Theory (RBT) by demonstrating that the true value of AI is unlocked when it is bundled with context-specific insights that align with circular economy goals.

Additionally, our findings on AI anxiety contribute to the socio-technical literature by demonstrating that psychological barriers, such as anxiety over job security, can negatively moderate the relationship between AI-generated insights and CEC. AI anxiety has often been overlooked in discussions about AI adoption, yet our results suggest that this human factor is essential in determining the adoption and implementation of AI within organizations [59]. By addressing this gap, we contribute to a deeper understanding of the social barriers limiting the full potential of AI in advancing sustainability goals [71].

8.1.4. Practical implications

For practitioners, this research underscores that AIC alone are insufficient to drive circular economy practices; DDI must be harnessed effectively for AIC to translate into sustainable business models. Managers should therefore prioritize the development of analytical capabilities alongside AI infrastructure. This entails fostering a culture in which employees are trained to generate, interpret, and apply insights from AI, as these are the levers that transform technical abilities into circular practices.

Furthermore, an effective AI adoption strategy should encompass both technological training and the psychological dimensions of change management (La [56]). Specifically, organizations must implement programs to mitigate AI anxiety and, hence, discourage resistance to fully embracing AI's benefits. Change-management strategies should incorporate both technical upskilling and mental-health support so that employees understand AI operations and the evolution of their roles, reducing fears of job displacement [85]. Addressing these socio-technical challenges will also help align AI initiatives with SDG 12 (Responsible Consumption and Production) and SDG 13 (Climate Action).

8.1.5. Limitations and future research

This study has several limitations that could be addressed in future research. First, the cross-sectional design limits our ability to establish a clear causal direction among AIC, DDI, and CEC. Future research should employ longitudinal designs to track the evolution of these relationships over time and to provide stronger causal inferences. Second, prior research [14] indicates that self-efficacy can moderate technology anxiety, suggesting that individuals with higher self-efficacy may experience less anxiety during AI implementation. Future studies could examine the interaction between self-efficacy and AI anxiety and its influence on the development and use of DDI, as our survey does not contain information on employee self-efficacy.

Similarly, although this study advances the analysis of AI adoption barriers by exploring socio-technical aspects our current model is necessarily limited in its exploration of other equally relevant, organization-specific moderators that influence the DDI to CEC relationship. Future research should therefore investigate a broader array of organizational factors across both the technical and social spheres. For instance, while we controlled for the macro-level factor of firm size, the internal technological readiness remains unexamined. Specific elements such as the complexity of the existing IT infrastructure or the maturity of the firm's data governance frameworks are instrumental in determining the capacity to generate and positively leverage DDI. On the social and managerial side, subsequent studies could explore how organizational culture and human resources management practices may effectively buffer the negative effect of technology-induced resistance, ensuring the smooth deployment and acceptance of AI-driven circular strategies.

Another limitation of this study is its constrained sample size. While our data incorporates firms from both the manufacturing and services sectors, the sample volume precludes conducting robust multi-group analysis to ascertain significant differences in the proposed model across these two distinct industrial contexts. Future scholarly work should prioritize large-scale data collection to facilitate such cross-sectional variation analysis, examining whether sector-specific characteristic. Furthermore, given that this study is situated solely within Colombia, an emerging economy, the findings may reflect a specific institutional context marked by unique technological maturity levels and market pressures. Subsequent research should aim to validate and potentially adjust this theoretical framework across a diverse range of economies, including those with advanced development statuses, to rigorously test the universality of the socio-technical friction points identified here.

Future studies should also expand on the socio-technical framework introduced here by examining additional human and organizational factors that may moderate the relationship between AI and sustainability outcomes. For example, exploring the influence of organizational culture on AI anxiety could yield valuable insights into how different environments either support or hinder AI adoption. Additionally, new strategies for managing the socio-technical challenges of AI implementation could be developed by investigating the role of governance frameworks in reducing AI anxiety.

Research could further investigate the broader social implications of AI, including how the digital divide and ethical AI governance impact the distribution of AI benefits across different societal groups. Understanding disparities in access to AI technology across industries and regions would be valuable for promoting equitable AI adoption.

Finally, longitudinal research is needed to disentangle the causal mechanisms linking AIC, DDI, and circular economy outcomes. Examining how organizations' capabilities evolve over time will provide deeper insights into how AIC translate into circular economy practices and sustainable business models.

9. Conclusion

This study sheds light on the intricate relationship between Artificial Intelligence Capabilities (AIC) and Circular Economy Capability (CEC), emphasizing the mediating role of Data-driven Insights (DDI) and the moderating effect of AI anxiety. By integrating socio-technical factors into the analysis, this research challenges the assumption that AIC alone drive sustainability outcomes. Instead, it reveals that AI's potential to foster circular economy practices is contingent upon how effectively organizations combine technical resources with actionable insights and address human resistance to AI adoption, acknowledging that successful implementation depends on overcoming training gaps and data vulnerabilities while integrating human-centric factors into digital strategies.

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work the authors used ChatGPT to check spelling and grammar and improve redaction. After using this tool/service, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

CRediT authorship contribution statement

Robinson Garcés-Marín: Writing – review & editing, Writing – original draft, Methodology, Formal analysis, Conceptualization. **José Arias-Pérez:** Writing – original draft, Methodology, Funding acquisition, Conceptualization. **Camilo Restrepo-Estrada:** Writing – review & editing, Writing – original draft, Methodology, Formal analysis, Conceptualization.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests:

Jose Arias-Perez reports financial support was provided by Colombian Ministry of Science, Technology and Innovation (Minciencias). Jose Arias-Perez reports financial support was provided by Colombian Institute of Educational Credit and Technical Studies Abroad (Icetex). If there are other authors, they 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. Scale items

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Constructs (Source)	Item	Questions
AI Capability (adapted from [66])	AIC1	We have explored or adopted cloud-based services for processing data and performing AI and machine learning.
	AIC2	We have the necessary processing power to support AI applications (e.g. CPUs, GPUs).

(continued on next page)

(*continued*)

Constructs (Source)	Item	Questions
	AIC3	We have invested in networking infrastructure (e.g. enterprise networks) that supports efficiency and scale of applications (scalability, high bandwidth, and low latency).
	AIC4	We have explored or adopted parallel computing approaches for AI data processing.
	AIC5	We have invested in advanced cloud services to allow complex AI abilities on simple API calls (e.g. Microsoft Cognitive Services, Google Cloud Vision).
Circular Economy Capability [94]	CEC1	Company is dedicated to reducing the consumption of raw materials and energy.
	CEC2	The company proactively enhances the energy efficiency of production equipment or that of equipment used in service delivery.
	CEC3	Recycling waste and garbage is reprocessed.
Data-Driven Insights (adapted from [37])	*Prescriptive insights*	
	Dat1	In my firm, there is a good prescriptive understanding of what should be done in relation to tasks at hand.
	Dat2	In my firm, there are good insights into the best course of action to improve future outcomes related to tasks at hand.
	Predictive insight	
	Dat3	In my firm, there is a good understanding of how the tasks at hand will lead to future outcomes.
	Dat4	In my firm, there is a good predictive understanding of possible future outcomes.
	Dat5	In my firm, there are good insights into each potential future outcome.
	Descriptive insight	
	Dat6	In my firm, the relationship between what has happened in the past and current tasks is well understood
	Dat7	In my firm, past issues related to tasks at hand are understood in detail.
	Dat8	In my firm, there is good insight into tasks at hand.
AI Anxiety (adapted from [92])		Regarding AI applications (e.g., ChatGPT, chatbots, virtual agents, or assistants) that are currently being used or are planned to be implemented in the company, employees in your organization:
	AIAnx1	Feel insecure about their ability to interpret AI-analyzed data outputs.
	AIAnx2	Are reluctant to use AI in the workplace.
	AIAnx3	Find learning about AI to be stressful.
	AIAnx4	Feel incapable of developing skills to effectively use AI.
	AIAnx5	Fear becoming dependent on AI and losing reasoning-based skills.
	AIAnx6	Feel unable to keep up with the latest developments in AI.
	AIAnx7	Would feel uncomfortable working with machines that are smarter than humans.
	AIAnx8	Feel incapable of understanding the basic technical aspects of AI.
	AIAnx9	Fear making mistakes when using AI in the workplace.
	AIAnx10	Avoid using AI tools because they find them intimidating.
	AIAnx11	Are unwilling to understand the benefits of AI for the business.

All constructs were operationalized with 5-point Likert scales (ranging from 1 = strongly disagree to 5 = strongly agree) and were directly coded, so that higher values reflect greater levels of the underlying construct.

Data availability

Data will be made available on request.

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