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Research article

Social innovation in SMEs: Examining the role of artificial intelligence and social and environmental sustainability☆

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A R T I C L E I N F O

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A B S T R A C T

This study examines how environmental sustainability, social sustainability, and artificial intelligence (AI) interact to foster social innovation in small and medium-sized enterprises (SMEs). Drawing on Resource-Based Theory (RBT) and Institutional Theory, it explores how internal resources, and external pressures jointly shape social innovation outcomes. Using a large dataset of more than 12,000 European SMEs, the study investigates the individual and combined effects of these practices. The findings reveal differential impacts among the three drivers. Social sustainability emerges as the most significant predictor of social innovation, highlighting its central role in generating social value and promoting equity and inclusion. Environmental sustainability also exerts a positive influence, contributing to the development of innovations that address both ecological and social challenges. In contrast, AI plays a more indirect role by enhancing efficiency, resource optimisation, and the implementation of sustainability strategies. Theoretically, the study advances understanding of social innovation in SMEs by integrating internal (RBT) and external (institutional theory) perspectives. It shows that innovation arises from the alignment of firm capabilities with institutional expectations. Practically, it offers guidance for SMEs and policymakers on how to integrate AI and sustainability to improve competitiveness while contributing to societal well-being.

1. Introduction

Social innovation refers to the development and implementation of novel solutions that address pressing social challenges while creating social value for individuals, communities, and society at large (Murray et al., 2010; Phills Jr et al., 2008). Unlike traditional innovation, which is often driven by technological or financial objectives, social innovation prioritizes social and environmental outcomes alongside economic considerations (Mulgan et al., 2007; Rao-Nicholson et al., 2017). Social innovation arises within the context of complex social challenges. These challenges are embedded in evolving socio-economic dynamics (Adomako and Nguyen, 2024; Erdiaw-Kwasie and Abunyewah, 2024; Van Wijk et al., 2019; Rao-Nicholson et al., 2017). In today's world, we confront a multitude of interconnected issues such as poverty, inequality, environmental degradation, and rapid technological change. Westley et al. (2017a,b) point out that these challenges often defy traditional solutions and call for innovative approaches that address their underlying causes and systemic complexities. The significance of social innovation lies in its ability to catalyze transformative change. It generates positive impacts on individuals, communities, and society as a whole (Purtik and Arenas, 2019; Altuna et al., 2015; Murray et al., 2010; Phills Jr et al., 2008). Through creativity, collaboration, and experimentation, social innovation offers new pathways to address persistent social problems and build more inclusive, equitable, and sustainable societies (Phills Jr et al., 2008; Benneworth and Cunha, 2015; Avelino et al., 2019; Van Wijk et al., 2019). Additionally, social innovation is essential for fostering resilience and adaptability in the face of uncertainty and rapid change.

In recent years, growing academic and managerial attention has focused on the intersection of artificial intelligence (AI), social sustainability, and environmental sustainability as key drivers of innovation (Mühlroth and Grottke, 2020; Truong and Papagiannidis, 2022). AI has rapidly transformed the way organizations generate and apply knowledge, while sustainability practices aim to ensure that such progress

☆ The data that support the findings of this study are available in the European Commission at https://www.gesis.org/en/eurobarometer-data-service/data-and-documentation/flash-eb.

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aligns with environmental protection and social well-being. Recent evidence suggests that AI increasingly complements environmental and social sustainability by enhancing resource efficiency, supporting responsible decision-making, and enabling new sustainable business models (e.g., Di Vaio et al., 2020; Fiorentino et al., 2020; Nishant et al., 2020; Gupta et al., 2023; Luo et al., 2024; Bibri et al., 2024). At the same time, social and environmental sustainability practices have become central to meeting stakeholder expectations, strengthening legitimacy, and generating broader societal benefits. The convergence of these dimensions offers fertile ground for examining how technology and sustainability interact to foster social innovation, opening opportunities to design business models that simultaneously enhance competitiveness and contribute to societal welfare.

However, despite this momentum, existing studies rarely examine these domains together. Much of the literature treats AI as a driver of operational or financial performance, while sustainability research often focuses on ethical responsibilities, regulatory compliance, or environmental outcomes (Garcia and Lee, 2018; Jones and Smith, 2020). Only a small number of studies explore their intersection, and even fewer investigate how AI, social sustainability, and environmental sustainability jointly influence social innovation. This fragmentation leaves a notable gap in understanding. Specifically, it remains unclear whether these practices operate independently or reinforce one another in generating social value.

Existing studies have largely explored AI as a driver of firm performance and competitiveness, or sustainability as a moral and regulatory imperative, but few have examined their combined effects on social innovation (Adams et al., 2017; Chen et al., 2018). Moreover, most research has focused on large corporations, overlooking small and medium-sized enterprises (SMEs), which differ in resources, structures, and social embeddedness. As a result, little is known about how SMEs integrate AI, social sustainability, and environmental sustainability to generate social innovation, or whether these practices operate as complementary or independent mechanisms.

This gap is especially relevant for small and medium-sized enterprises (SMEs). SMEs form the backbone of the European economy, accounting for over 99 % of firms and 94 million jobs (World Bank Finance, 2021) and are deeply embedded in local communities. This positioning makes them natural engines of social innovation. Yet SMEs also confront constraints such as limited financial and human capital, skill shortages, and growing institutional pressures for responsible and sustainable behaviour (Holl and Rama, 2024; Kumar et al., 2020; Dubey et al., 2019; Gerrikagoitia et al., 2019; Ancarani and Di Mauro, 2018; Bag et al., 2022). Balancing innovation adoption with sustainability commitments is therefore more challenging for SMEs than for larger firms. At the same time, it is potentially more consequential. Despite this, empirical research examining how SMEs integrate AI and sustainability to develop social innovation remains extremely limited.

To address this gap, this study examines how AI adoption, environmental sustainability, and social sustainability influence the development of social innovation among SMEs, and whether these practices act as complements or substitutes.

To frame this analysis, we draw on the Resource-Based Theory (RBT) (Barney, 1991; Wernerfelt, 1984) and the Institutional Theory (DiMaggio and Powell, 1983; Scott, 1995). RBT explains how firm-specific resources and capabilities, such as technological know-how, organizational culture, and stakeholder relationships, can be mobilized to create sustainable competitive advantage and social value. However, RBT alone says little about why SMEs choose to invest in these capabilities despite resource constraints. Institutional Theory complements this view by highlighting how external pressures for legitimacy, such as regulations, norms, and stakeholder expectations, influence the adoption of AI and sustainability practices. Yet, on its own, it cannot explain why these practices lead to different innovation outcomes across firms. The combination of both perspectives allows us to capture the complementary roles of internal capabilities and external pressures.

To investigate these relationships, we analyse a representative sample of 12,108 SMEs from Eurostat's Flash Eurobarometer (2020). Using weighted logistic regressions, we assess the individual and joint effects of AI, environmental sustainability, and social sustainability on social innovation.

This study contributes to the literature on sustainability and (social) innovation in several ways. First, we show that social innovation in SMEs depends on the alignment of technological capabilities with sustainability-oriented practices. Second, we advance research in this area by evidencing that AI alone is insufficient as its benefits materialise when embedded within strong social and environmental sustainability strategies, thereby laying out new avenues for future research and for policy makers and practitioners decision making.

2. Theoretical framework: Resource-Based Theory and Institutional Theory

To understand how SMEs integrate artificial intelligence, social sustainability, and environmental sustainability to foster social innovation, this study draws on two complementary theoretical perspectives: Resource-Based Theory (RBT) and Institutional Theory (IT). Individually, each theory explains only part of the phenomenon. RBT accounts for the internal capabilities that enable SMEs to transform technologies and sustainability routines into innovative outputs, but it is largely silent on why firms choose to develop these capabilities in the first place. In contrast, IT explains the external pressures (regulatory, normative, and mimetic) that compel firms to adopt sustainability and AI practices, yet it cannot explain which firms actually convert adoption into meaningful innovation.

Bringing RBT and IT together therefore fills a core conceptual gap: it links the motivation to adopt AI and sustainability practices (IT) with the ability to leverage them for social innovation (RBT). This integration is especially important in the SME context, where institutional pressures frequently trigger adoption, but resource constraints determine whether adoption results in symbolic compliance or genuine innovation. Thus, the framework captures (i) how external demands for digitalisation and sustainability push SMEs to adopt new practices, and (ii) how internal technological, environmental, and social capabilities shape their capacity to recombine these practices into socially innovative solutions (see Fig. 1).

2.1. Resource-Based Theory (RBT)

The Resource-Based Theory explains competitive advantage as the outcome of a firm's ability to acquire, develop, and deploy resources that are valuable, rare, inimitable, and non-substitutable (Barney, 1991; Wernerfelt, 1984). These resources may be tangible, such as financial capital, physical assets, or technologies, or intangible, such as organizational culture, managerial know-how, or relational capital with stakeholders. A key advance of RBT is that it conceptualizes advantage not as the possession of isolated assets, but as the bundling and recombination of heterogeneous resources into higher-order capabilities (Grant, 1991; Teece et al., 1997). This perspective is especially relevant for sustainability- and AI-related innovation. Such innovation depends on a firm's ability to integrate technological, human, and organizational resources into coherent capability systems rather than treat them as standalone tools.

For SMEs, RBT is particularly meaningful because resource scarcity (e.g. financial, technological, and human) forces firms to rely on idiosyncratic internal strengths such as agility, embedded stakeholder relationships, and specialized sustainability or community knowledge (Beckmann et al., 2023; Jafari-Sadeghi et al., 2022). These attributes allow SMEs to mobilise knowledge quickly, experiment with new practices, and respond to emerging needs more nimbly than larger firms (Chan et al., 2019; Jafari-Sadeghi et al., 2022). Such agility can transform modest resource endowments into meaningful sources of

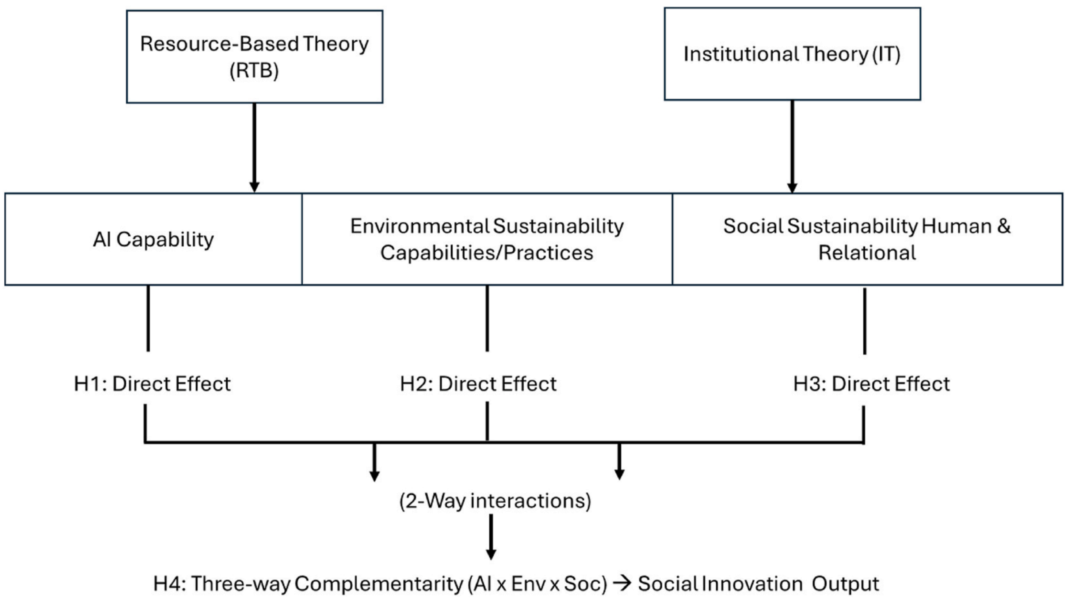

Fig. 1. Conceptual framework.

advantage when they are effectively integrated and aligned with strategic goals.

RBT also provides a foundation for understanding how SMEs generate social innovation. RBT suggests that SMEs can transform both tangible and intangible resources into solutions that create social value. Employees' skills and commitment, relational networks, and organizational cultures of responsibility can serve as unique resources for developing socially innovative products, services, or practices (Murray et al., 2010; Purcarea et al., 2013). Firms with a strong culture of inclusivity may be better positioned to design socially responsible employment practices, while those with environmental expertise may innovate in sustainable production processes. However, SMEs' resource limitations also impose constraints: balancing investments in social innovation with the need for economic viability requires careful resource orchestration (O'Cass and Sok, 2014; Westley et al., 2017a,b).

In this study, AI adoption, social sustainability, and environmental sustainability are conceptualized as distinct capability domains that expand the internal resource base of SMEs. Recent SME-focused research further supports conceptualising AI adoption and sustainability practices as capability-based drivers of innovation rather than isolated technological or managerial actions. Studies show that innovation capability in SMEs emerges from the integration of digital technologies, knowledge processes, and organisational routines. Together, these elements shape firms' ability to generate sustainability-oriented innovation outcomes (Mikalef et al., 2021; Peretz-Andersson et al., 2024). In this perspective, innovation is not defined by technological sophistication alone, but by the firm's capacity to mobilise limited resources into effective learning, coordination, and adaptive practices aligned with social and environmental objectives (Achmad et al., 2023; Achmad and Wiratmadja, 2025). Building on this capability-based view, recent empirical work indicates that AI adoption in SMEs operates as an enabling digital capability that enhances information processing, learning, and decision-making, even at early or limited stages of adoption, thereby strengthening innovation capability and supporting sustainability-oriented innovation outcomes (Achmad et al., 2023; Achmad and Wiratmadja, 2025; Nazarian et al., 2024). Similarly, social and environmental sustainability practices contribute to innovation by forming complementary capability bundles that strengthen human, relational, and operational resources under SME resource constraints (Achmad et al., 2023; Achmad and Wiratmadja, 2025; Rumanti et al., 2020).

Although social and environmental sustainability are interconnected in practice, they are treated in this study as analytically distinct dimensions for theoretical and empirical purposes. Social sustainability is conceptualized as firm-level practices addressing the social dimension of sustainability through investments in human and relational capital, while environmental sustainability captures a separate set of practices related to operational and ecological routines aimed at managing environmental impacts (Dyllick and Hockerts, 2002; Hart, 1995). Each domain contributes different types of valuable, rare and difficult-to-imitate resources that shape how firms accumulate knowledge, coordinate activity, and manage operations.

AI adoption constitutes an information-processing and analytical capability, enabling firms to handle data, automate tasks, recognise patterns, and support decision processes (Wang and Zhang, 2025). Research shows that AI enhances both exploitative learning routines and exploratory knowledge functions, strengthening a firm's ability to sense, interpret and use information (Sjödin et al., 2023; Bag et al., 2021). For SMEs, where cognitive, analytical and computational resources are typically constrained, AI functions as a capability amplifier by expanding their processing and learning capacity (Gupta, 2024).

Social sustainability develops human and relational capital, core intangible resources emphasized in RBT. Practices such as fair working conditions, diversity and inclusion initiatives, employee development, and community engagement build trust, cohesion and organisational identification (Aguinis and Glavas, 2012; Barrena-Martínez et al., 2019). These practices enhance collaboration, encourage knowledge exchange and strengthen stakeholder relationships, forming relational assets that are embedded, path-dependent and difficult for competitors to replicate (Russo and Perrini, 2010). In SMEs, where interpersonal ties, tacit knowledge and internal culture play a central role, such practices reinforce a stable and engaged resource base (Delmas and Pekovic, 2018; Littlewood and Holt, 2018).

Environmental sustainability reflects a set of environmental capabilities grounded in routines for resource efficiency, pollution reduction, eco-design, waste minimisation and circular economy practices (Hart, 1995; Aragón-Correa and Sharma, 2003). These capabilities represent operational knowledge and procedural routines that become embedded over time and are costly for other firms to imitate. The environmental-management literature emphasises that environmental capabilities build technical expertise, process discipline and reputational assets that form part of a firm's long-term capability base (Porter and van der Linde, 1995; Schaltegger and Wagner, 2011). In SMEs, these practices often reflect accumulated experiential knowledge, local constraints and firm-specific routines, making them highly idiosyncratic.

2.2. Institutional Theory (IT)

Institutional Theory explains how organizational behavior is shaped not only by efficiency considerations but also by pressures to conform to prevailing norms, regulations, and cultural expectations in order to secure legitimacy (DiMaggio and Powell, 1983; Scott, 1995). Institutions are understood as the "rules of the game," providing the regulative, normative, and cultural–cognitive frameworks that guide organizational conduct. Firms adopt certain practices because they are perceived as legitimate, appropriate, or taken for granted within their institutional environment, even when the immediate efficiency benefits are not obvious.

According to Scott's (1995) influential framework, institutions consist of three pillars. The regulative pillar encompasses formal rules, laws, and policies that constrain or enable organizational choices. The normative pillar refers to values, professional standards, and societal expectations that prescribe appropriate behaviors. The cultural–cognitive pillar reflects shared understandings and taken-for-granted assumptions about what constitutes legitimate organizational action. Together, these pillars create coercive, normative, and mimetic pressures that drive organizations toward homogeneity within organizational fields (DiMaggio and Powell, 1983).

For SMEs, institutional pressures are particularly significant because of their limited resources vulnerability to external shocks, and dependence on legitimacy in local markets. SMEs often operate under strong coercive pressures from regulatory frameworks, such as environmental regulation, digitalisation directives, and compliance requirements from EU legislation (e.g., the EU Green Deal, Circular Economy Action Plan, and digital transformation policies). Normative pressures arise from growing expectations among customers, employees, supply-chain partners and local communities that push SMEs toward adopting socially responsible and sustainable practices. SMEs also face mimetic pressures, particularly in innovation adoption since industry leaders and larger firms implement AI and sustainability practices, as SMEs imitate these trends to maintain legitimacy and avoid being perceived as outdated or irresponsible. Recent work shows that such institutional forces increasingly shape SMEs' sustainability and digital transformation trajectories (Dubey, 2025; Torrent-Sellens et al., 2025; Bag et al., 2021).

Applied to this study, Institutional Theory suggests that SMEs adopt AI, environmental sustainability, and social sustainability not solely as strategic or efficiency-driven choices, but also as responses to coercive, normative, and mimetic pressures within their institutional environments. AI adoption, for example, is often influenced by mimetic pressures to align with industry-wide digitalisation trajectories and to meet emerging expectations regarding technological modernity, data transparency, and digital competitiveness, patterns increasingly documented in European SMEs (Dubey, 2025; Torrent-Sellens et al., 2025). Environmental sustainability practices, in turn, frequently arise from coercive pressures generated by regulatory frameworks related to pollution control, waste management, and resource efficiency, reflecting longstanding institutional influences described in the environmental management literature (Porter and van der Linde, 1995; Schaltegger and Wagner, 2011). Social sustainability is shaped primarily by normative pressures linked to societal expectations for fair treatment, workplace inclusion, employee welfare, and ethical governance. These expectations increasingly permeate SME environments through stakeholder demands and EU-level social directives, reinforcing the role of socially responsible practices as markers of organisational legitimacy (Aguinis and Glavas, 2012; Barrena-Martínez et al., 2019).

However, IT emphasises that adoption driven by legitimacy concerns does not necessarily imply deep implementation. Firms may comply symbolically, adopting policies or practices for appearance rather than substantive change (Hyatt and Berente, 2017). Thus, institutional compliance alone does not guarantee social innovation. Whether external pressures translate into meaningful outcomes depends on a firm's internal resources and capabilities, including its knowledge base, absorptive capacity, and stakeholder relationships. SMEs with stronger internal capacities are better positioned to move beyond symbolic compliance and transform institutional expectations into substantive practices—such as integrating AI meaningfully, implementing advanced environmental routines, or embedding social responsibility into organisational processes.

3. Hypotheses

3.1. The effect of artificial intelligence (AI) on social innovation

AI embodies the integration of advanced algorithms and computational systems designed to perform tasks that typically require human intelligence (Jones and Smith, 2019; Johnson and White, 2021). This includes learning from data, making decisions, solving complex problems, and understanding natural language. As digitalisation intensifies across industries, AI has come to represent both a technological resource and an organisational capability that enables firms to interpret information, coordinate activities, and respond to complex economic, social, and environmental challenges (Ardito, 2023; Wang et al., 2023, 2024). For instance, through machine learning, companies can analyse vast amounts of data to identify patterns and insights that inform better decision-making, optimize supply chains, forecast demand, and personalize services (Lee et al., 2017; Chhillar and Aguilera, 2022; Brown and Miller, 2018).

For SMEs, whose innovation activities are constrained by limited analytical skills and managerial capacity, AI provides a capability that enhances how firms search for, interpret, and respond to complex social problems. Social innovation often requires processing diverse forms of information: community needs, behavioural patterns, stakeholder concerns, and context-specific social dynamics. AI assists in this process by expanding the firm's ability to collect, organise, and analyse dispersed and unstructured data, thereby improving problem sensing and need identification (Chen et al., 2018; Garcia and Lee, 2018).

From an RBT perspective, this means AI strengthens both exploitative and exploratory learning routines. It improves operational efficiency, freeing managerial resources, while also enabling SMEs to recognise emerging social issues and interpret weak signals that would otherwise remain unnoticed (Teece, 2007; Sjödin et al., 2023). These enhanced sensing and analytical capabilities do not constitute social innovation themselves, but they enrich the resource base (e.g. data-processing capability, pattern-recognition capability, and diagnostic capability) that SMEs draw upon when designing socially oriented solutions (Adams et al., 2017; Gupta, 2024). This positions AI as a capability that supports the upstream activities that precede social innovation: identifying needs, understanding affected stakeholders, evaluating alternative responses, and coordinating resources. In SMEs, where these cognitive and analytical tasks are usually difficult to perform due to resource scarcity, AI therefore becomes an enabling capability that strengthens the informational foundations from which social innovation can be developed.

SMEs adopt AI not only because it offers internal efficiency gains but also because external expectations increasingly frame digitalisation as an appropriate and legitimate organisational practice. Coercive, normative and mimetic pressures are particularly salient for SMEs because of their heightened dependence on external legitimacy and trust. Unlike large firms, SMEs often lack formalised governance structures and therefore rely more strongly on their reputational and relational standing within their ecosystems (Aguinis and Glavas, 2012; Barrena-Martínez et al., 2019). In this environment, AI can function as a legitimacy-enabling practice: it allows SMEs to meet expectations for transparency, data governance, and modernised operational routines.

Beyond adoption pressures, AI also shapes the institutional conditions under which SMEs engage with stakeholders. AI enables more systematic analysis of communication channels, customer feedback, and community inputs, which supports practices of consultation, participation, and dialogue that stakeholders increasingly view as necessary for responsible organisational conduct (Johnson and White, 2021). These communication and transparency capabilities help SMEs align their activities with prevailing societal norms, making their responses more contextually grounded and institutionally acceptable. Moreover, AI-facilitated monitoring and reporting systems allow firms to demonstrate outcomes and compliance more convincingly, satisfying legitimacy requirements for accountability and disclosure (Adams et al., 2017).

Taken together, the integration of RBT and IT suggests that AI contributes to social innovation only when SMEs' analytical capabilities interact with institutional pressures for responsible and transparent digitalisation. AI expands the firm's capacity to sense social problems and analyse stakeholder needs, but institutional pressures determine which problems are prioritized and why certain socially oriented solutions gain legitimacy. Thus, institutional forces channel the enhanced informational and learning capabilities provided by AI toward socially valued outcomes rather than merely efficiency-driven uses. Social innovation arises when these capability enhancements (RBT) are aligned with legitimacy requirements and societal expectations (IT). Hence, we propose.

Hypothesis 1. AI adoption positively impacts the development of social innovation in SMEs.

3.2. *The effect of environmental sustainability in an SME on social innovation*

The integration of environmental sustainability into the activities of SMEs can significantly enhance their capacity to engage in innovative responses to social and ecological challenges. Environmental practices, such as resource efficiency, pollution prevention, and waste reduction, constitute not only contributions to ecological protection but also organisational routines that stimulate learning, problem solving, and long-term value creation (Hafeez et al., 2024; Schaltegger and Wagner, 2011). Environmental sustainability therefore operates simultaneously as a response to external demands and as a source of strategic capabilities that can indirectly contribute to socially oriented innovation.

From a RBT perspective, environmental-management routines represent valuable and hard-to-imitate capabilities. Established research shows that eco-efficiency, pollution-prevention competences, and circular-economy routines can reduce operational risk, enhance efficiency, and open new technological and organisational opportunities (Aragón-Correa and Sharma, 2003; Heikkurinen et al., 2019; Triguero et al., 2022). In SMEs, such practices can free scarce resources, strengthen process knowledge, and enhance reputational capital, thereby expanding the capacity to pursue additional innovation activities. Developing eco-friendly products or implementing clean-production processes also generates technical knowledge and problem-solving skills that can later be leveraged for socially oriented innovations.

From an Institutional Theory perspective, SMEs face strong coercive pressures from EU environmental regulation, normative pressures from communities, customers, and employees expecting responsible ecological behaviour, and mimetic pressures to emulate sustainability leaders in their industries. These external forces encourage SMEs to adopt environmental practices as part of maintaining legitimacy (Schaltegger and Wagner, 2011; Bakos et al., 2020; Tyler et al., 2024). Because SMEs are highly dependent on their reputational standing and stakeholder trust, compliance with environmental expectations often becomes a precondition for continued market participation.

The alignment of internal environmental capabilities with these institutional expectations creates conditions conducive to broader forms of innovation, including those with social objectives. For instance, resource-efficiency measures may yield knowledge that can be repurposed to address local social problems (e.g., community access to clean water, reduction of harmful emissions). Likewise, engagement in environmental initiatives often requires collaboration with public agencies, NGOs, and supply-chain partners, which can provide SMEs with access to additional knowledge, networks, and legitimacy that indirectly support social innovation efforts (Scherer and Palazzo, 2011; Mirvis et al., 2016).

Therefore, environmental sustainability functions as both an internal capability and an institutionalized organisational expectation, shaping the context in which SMEs identify, frame, and respond to social needs. Environmental capabilities generate resource efficiencies, eco-knowledge, and problem-solving routines (RBT), while institutional pressures define the environmental and societal problems that firms are expected to address (IT). Social innovation emerges when SMEs use their environmental routines not only to comply with external expectations but to reinterpret these expectations into novel solutions that provide social and ecological benefits. Institutional pressures therefore amplify and direct the innovative potential of environmental capabilities by signalling which environmental–social problems are legitimate and urgent. When these dimensions reinforce each other, SMEs are better positioned to produce innovations that address environmental challenges while also generating social value. Hence, we propose.

Hypothesis 2. Environmental sustainability practices positively affect the development of social innovation in SMEs.

3.3. *The impact of social sustainability within an SME on social innovation*

Social sustainability emphasises human well-being, equity, and inclusion (Dempsey et al., 2011; Bakos et al., 2020). It includes practices such as improving working conditions, promoting diversity, and ensuring fair and responsible stakeholder relationships. These practices create long-term value for both organizations and society and with global social priorities such as the Sustainable Development Goals and broader societal concerns around inequality, fairness, and environmental justice (UNDP, 2015; Di Vaio et al., 2020).

From an RBT perspective, social sustainability generates intangible resources such as enhanced employee commitment, psychological safety, relational trust, and organizational culture, and value-driven organizational culture, which are difficult for competitors to imitate (Aguinis and Glavas, 2012; Barrena-Martínez et al., 2019). These human and relational assets strengthen collaboration, facilitate knowledge exchange, and increase employees' willingness to engage in problem solving, which are foundational conditions for the generation of socially oriented ideas (Murray et al., 2010; Purcarea et al., 2013). For example, SMEs with inclusive and participatory organizational environments build internal climates that support initiative taking, creativity, and co-creation, which heighten their capacity to detect and address social needs.

From an Institutional Theory perspective, SMEs also face normative pressures from employees, communities, NGOs, and professional bodies to adopt socially responsible practices (Dubey et al., 2019; Ferraro and Gao, 2018; Schwartz et al., 2019). Expectations for diversity, equity, fair treatment, and transparent governance are now embedded in European regulatory and societal frameworks. Because SMEs depend more heavily than large firms on legitimacy within their immediate communities, these normative pressures strongly shape their adoption of socially responsible practices. Social sustainability thus functions as an institutionalized expectation that SMEs must meet to retain legitimacy and stakeholder support.

The transformation of these practices into social innovation occurs when internal capabilities align with institutional pressures. For example, compliance with fair-labour or inclusion standards can evolve into innovative employment, training, or governance models if SMEs possess the relational networks and absorptive capacity needed to reinterpret institutional demands into new practices. Similarly, building strong stakeholder relationships facilitates collaborative problem solving with community organizations, NGOs, or public institutions, which can expand access to external knowledge, resources, and new opportunities for socially oriented projects (Longoni et al., 2018; Graves and Sarkis, 2018).

The combination of RBT and IT suggests that social sustainability drives social innovation when internally developed human and relational capabilities are mobilized in response to external expectations for fairness, inclusion, and responsible governance. Social sustainability builds collaborative capacity, trust, and stakeholder relationships internally (RBT), but institutional pressures define which social problems require action and legitimise organisational efforts to address them (IT). Social innovation therefore arises when these internal relational assets are aligned with societal expectations, enabling SMEs to translate values-driven practices into novel solutions with social impact. Hence, we propose.

Hypothesis 3. Social sustainability practices positively affect the development of social innovation in SMEs.

3.4. The joint effect of environmental and social sustainability with AI on social innovation

Environmental sustainability, social sustainability and AI each contribute distinct but related capabilities to SMEs. Environmental practices build eco-efficiency, pollution-prevention and circular-economy routines; social sustainability develops human and relational capital rooted in fairness, participation and inclusion; AI enhances analytical, sensing and coordination capabilities. While each domain can individually support innovation, complex social problems typically cut across ecological, social and technological dimensions, suggesting that their combined deployment may be more powerful than the sum of their separate effects (Hanelt et al., 2021; Torrent-Sellens et al., 2025).

From a Resource-Based Theory perspective, synergy arises when different capabilities interact in ways that make their joint effect superadditive (Milgrom and Roberts, 1990; Teece, 2007). Environmental sustainability equips SMEs with technical knowledge about resource use, emissions, waste streams and process redesign (Aragón-Correa and Sharma, 2003; Bakos et al., 2020). Social sustainability develops trust, collaboration, and participatory routines that facilitate dialogue with employees and communities (Aguinis and Glavas, 2012; Barrena-Martínez et al., 2019). AI, in turn, provides the ability to process large amounts of operational and stakeholder data, detect patterns and simulate alternative courses of action (Adams et al., 2017; Sjödin et al., 2023).

Taken together, these capabilities are complementary rather than redundant. Environmental capabilities define what ecological problems can be tackled; social capabilities shape with whom and how problems are addressed; AI capabilities influence how effectively information is processed and solutions are designed. For example, an SME that monitors energy consumption and emissions (environmental capability), engages employees and local communities in identifying impacts (social capability), and uses AI to analyse usage data and feedback (AI capability) is better positioned to design socially innovative solutions such as community energy-sharing schemes or targeted support for vulnerable groups affected by energy poverty. In RBT terms, the marginal value of each capability is higher when the others are present, consistent with the notion of supermodularity where the incremental benefit of one activity (e.g. AI) is greater when the levels of the other activities (environmental and social sustainability) are higher (Milgrom and Roberts, 1990).

From an Institutional Theory perspective, external pressures increasingly arrive "bundled" as well. EU policy frameworks simultaneously promote digitalisation, decarbonisation and social inclusion (e.g. Green Deal, Digital Strategy, Social Pillar). SMEs are thus exposed to overlapping coercive pressures (regulations, reporting obligations), normative pressures (stakeholder expectations for responsibility, fairness and transparency) and mimetic pressures (imitation of sustainability and digital frontrunners) (Scott, 1995; Dubey, 2025). In this context, adopting AI or sustainability in isolation may be insufficient: legitimacy increasingly depends on demonstrating that technological modernisation, environmental responsibility and social justice are pursued together (Schaltegger and Wagner, 2011; Torrent-Sellens et al., 2025).

AI further interacts with sustainability practices on the institutional side. When environmental and social commitments are in place, AI strengthens a firm's ability to document, communicate and verify its impacts through more granular monitoring, reporting and stakeholder engagement (Adams et al., 2017; Johnson and White, 2021). Conversely, strong environmental and social orientations help to anchor AI use in socially legitimate purposes, reducing concerns about purely efficiency-driven or opportunistic applications (Bag et al., 2021; Wang and Zhang, 2025). This mutual reinforcement implies that AI-enabled innovations are more likely to be viewed as appropriate and trustworthy when they are embedded in credible sustainability practices, while sustainability efforts become more visible, scalable and adaptive when supported by AI analytics.

Taken together, RBT and IT suggest that the joint effect of AI, environmental sustainability and social sustainability on social innovation is expected to be synergistic rather than merely additive. Internally, the three domains form a complementary capability bundle that combines ecological know-how, human and relational capital, and data-processing power. Externally, institutional pressures reward firms that align technological adoption with environmental and social commitments, increasing the legitimacy and diffusion potential of resulting innovations. In such a configuration, the incremental contribution of AI to social innovation should be larger at higher levels of environmental and social sustainability, and vice versa, consistent with a supermodular relationship among these practices. Hence, we propose.

Hypothesis 4. The combination of environmental sustainability, social sustainability, and AI adoption synergistically enhances the development of social innovation in SMEs.

4. Methods and data

4.1. Database

To empirically investigate the hypotheses, we analysed data from Eurostat's Eurobarometer Flash No. 486, commissioned by the European Commission (Eurostat, 2022). This survey, conducted between February and May 2020, investigates various topics, including innovation and digital technologies. Interviews, conducted in their respective national languages, were carried out over the phone and standardized by the European Commission, and robustness checks were performed to assess consistency across subsamples. As this study specifically targets SMEs in Europe, the sample used comprises 12,108 SMEs. The geographical scope of the database covers the 27 EU countries. Stratified sampling ensured representativeness in terms of firm size, industry, and geography, providing a comprehensive view of the SME population in Europe. Tables 1 and 2 depict the sample distribution by size and geographical

Table 1
Sample size distribution.

Employees	Frequency	Per cent
1 to 9	7708	63.7
10 to 49	2571	21.2
50 to 250	1829	15.1
Total	**12,108**	**100.0**

Table 2
Sample geographical distribution.

Countries	Frequency	Per cent
FR - France	485	4.0
BE - Belgium	475	3.9
NL - The Netherlands	474	3.9
DE - Germany	479	4.0
IT - Italy	476	3.9
LU - Luxembourg	195	1.6
DK - Denmark	479	4.0
IE - Ireland	475	3.9
GR - Greece	482	4.0
ES -Spain	476	3.9
PT - Portugal	479	4.0
FI - Finland	476	3.9
SE - Sweden	476	3.9
AT - Austria	470	3.9
CY - Cyprus (Republic)	201	1.7
CZ - Czech Republic	482	4.0
EE - Estonia	484	4.0
HU - Hungary	481	4.0
LV - Latvia	489	4.0
LT - Lithuania	481	4.0
MT - Malta	201	1.7
PL - Poland	475	3.9
SK - Slovakia	492	4.1
SI - Slovenia	488	4.0
BG - Bulgaria	476	3.9
RO - Romania	479	4.0
HR - Croatia	482	4.0
Total	**12,108**	**100.0**

region.

4.2. Measures

The first independent variable concerns the implementation of environmental practices within SMEs. Environmental sustainability is measured using items capturing firm-level environmental practices, including resource efficiency, waste reduction, and actions aimed at reducing environmental impact. This construct reflects the operational and ecological dimension of sustainability, focusing on the adoption of environmentally responsible processes and routines (Hart, 1995; Bansal and Roth, 2000). This measure captures practices aimed at managing natural resources and environmental externalities rather than social or stakeholder outcomes. The specific inquiry is: Regarding environmental sustainability, which of the following actions, if any, is your enterprise actively pursuing?: i) Recycling or reusing materials; ii) Reducing consumption of natural resources or minimizing the impact on the environment (e.g., water conservation or transitioning to sustainable resources); iii) Conserving energy or transitioning to sustainable energy sources; and iv) Developing sustainable products or services. To measure the environmental sustainability in SMEs, we created the variable *environmental,* constructed as a cumulative index of four types of activities (Cronbach's Alpha: 0.685).

The second independent variable pertains to the development of social sustainability initiatives within SMEs. Social sustainability is operationalised using survey items capturing firm-level practices related to employee well-being, social inclusion, and social responsibility. Consistent with the sustainability literature, this construct reflects the extent to which firms address the social dimension of sustainability by investing in human and relational capital, including workforce conditions and socially responsible practices (Dyllick and Hockerts, 2002; Bansal, 2005). The measure focuses on internal and stakeholder-oriented social practices. In particular, the question asked is: Regarding social sustainability, which of the following actions, if any, is your enterprise actively undertaking?: i) Enhancing working conditions for employees; ii) Promoting diversity and equality in the workplace; iii) Assessing the societal impact of the enterprise; and iv) Involving employees in the governance of the enterprise. Similar to the previous variable, the variable *sustainability* was constructed as a cumulative index of four types of items (Cronbach's Alpha: 0.723).

The third independent variable concerns the adoption of AI (*AI*). AI adoption is measured as a binary variable indicating whether the enterprise has adopted AI-based tools or applications in its operations. This measure captures functional adoption rather than technological intensity, investment level, or AI maturity. Accordingly, AI adoption is interpreted as an indicator of emerging digital capability, reflecting whether firms have begun integrating AI into organisational processes. This operationalisation is consistent with SME-focused research, where early-stage or selective AI use constitutes a meaningful capability despite limited scale or sophistication (Mikalef et al., 2021; Peretz-Andersson et al., 2024).

As for the dependent variable, we consider social innovation (*social innovation*). Social innovation is operationalised using a binary indicator derived from the Flash Eurobarometer 486 survey, capturing whether the enterprise has introduced innovations with explicit social objectives. Consistent with prior research on social innovation in SMEs, this measure reflects the presence of socially oriented innovation activities aimed at generating social value, rather than distinguishing between specific innovation types such as product, process, or business-model innovation (Phills Jr et al., 2008; Murray et al., 2010; Rao-Nicholson et al., 2017; Van Wijk et al., 2019). The operationalisation therefore adopts an outcome-oriented perspective, focusing on the social purpose and impact of innovation rather than its technological or organisational form. This approach is appropriate in large-scale SME surveys (e.g. Eurostat, 2018; Mulgan et al., 2007), where the social orientation of innovation is more salient than fine-grained typologies and aligns with established definitions of social innovation as innovation primarily aimed at generating social value. The variable is binary, where 1 denotes the development of social innovation and 0 indicates its absence.

Additionally, we have incorporated several control variables. These control variables address internal aspects of SMEs, including size, company age, level of digitalisation, ecosystem support for business operations, ease of establishing collaborations, and access to skills. Table A1 provides a detailed overview of the variables definitions.

4.3. Methodology

To empirically test the hypotheses developed in this study, we adopt a quantitative research design based on multivariate regression models, supported by extensive robustness checks. The survey design of Flash Eurobarometer 486 includes sampling weights (w1) correcting for unequal selection probabilities, which we include in our estimations in addition to standard errors clustered at the country level to account for the multi-stage sampling and intra-country correlation.

To address potential sample heterogeneity and ensure that results are not driven by sectoral composition or overfitting, we additionally conduct analyses across (i) manufacturing vs. services subsamples, (ii) 70/30 train–test partitions for out-of-sample validation, and (iii) procedures addressing possible common-method variance and endogeneity, detailed in Section 4.4.

To examine the influence of AI adoption, environmental sustainability practices, and social sustainability practices on the likelihood that an SME develops social innovation (Hypotheses H1–H3), we estimate logistic regression models of the form:

$$\text{Social Innovation}_i = \alpha + \beta_1\, \text{AI}_i + \beta_2\, \text{Environmental}_i + \beta_3\, \text{Social}_i + \gamma X_i + \varepsilon_i$$

where *Social Innovation* is a binary outcome and *AI*, *Environmental*, and *Social* denote the three main explanatory variables. The vector X_i includes SME size, digitalisation, ecosystem support, collaboration capability, skill availability, and survey year.

To assess whether AI adoption enhances the effects of environmental and social sustainability practices on social innovation (synergy or complementarity), we incorporate two-way and three-way interaction terms:

$$\text{Social Innovation}_i = \alpha + \beta_1\ \text{AI}_i + \beta_2\ \text{Environmental}_i + \beta_3\ \text{Social}_i + \beta_4\ \text{AI}_i{}^*\text{Environmental}_i + \beta_5\ \text{AI}_i{}^*\text{Social}_i + \beta_3\ \text{Environmental}_i{}^*\text{Social}_i + \gamma X_i + \varepsilon_i$$

Interaction effects are interpreted using marginal effects, simple slope analysis, and predicted probabilities, following standard practice (Ai and Norton, 2003; Karaca-Mandic et al., 2012). In particular, we compute average marginal effects (AMEs), conditional marginal effects at representative values.

To test whether complementarities satisfy the formal condition of supermodularity, relevant to Hypothesis H4, we compute the inequality (Milgrom and Roberts, 1990):

$$[f\ (\text{Env}_H, \text{Soc}_H, \text{AI} = 1) - f\ (\text{Env}_H, \text{Soc}_L, \text{AI} = 1)] > [(\text{Env}_L, \text{Soc}_H, \text{AI} = 1) - (\text{Env}_L, \text{Soc}_L, \text{AI} = 1)]$$

where $f(x,y)$ represents the predicted probability of social innovation when the pair of practices (x,y) take values 0 or 1. Predicted probabilities are estimated from the logistic models, and standard errors for the supermodularity contrast are obtained using the delta method.

4.4. Robustness checks

Given the cross-sectional and self-reported nature of the Eurobarometer dataset, we implement a series of methodological robustness checks to ensure that our findings are not driven by common-method variance, endogeneity, unobserved confounding, model miscalibration, or measurement issues in the sustainability indices. The results from these tests are presented in section 5.1 (robustness checks and further results).

First, because all focal variables are drawn from the same survey instrument, we address common method variance by including a marker variable in the regression (Podsakoff et al., 2003). Marker variables serve as theoretically unrelated indicators that capture any shared method variance arising from respondents using the same survey instrument. We use “Payment delays”, which comes from a question battery asking firms to identify general business obstacles. This item refers to liquidity and cash-flow problems and is theoretically unrelated to AI adoption, environmental sustainability, social sustainability, or social innovation. Because it represents an external operational problem, it satisfies the criterion of cognitive and conceptual separation required for marker variables. We add this marker as an additional regressor to the main logit specification to capture any shared method variance that is not substantively linked to the constructs of interest. If common method bias were severe, the marker would load significantly, and its inclusion would materially alter the coefficients of AI, environmental sustainability or social sustainability.

Second, we examine potential endogeneity between AI adoption, sustainability practices, and social innovation using a Two-Stage Residual Inclusion (2SRI) estimator. In nonlinear models such as logit, 2SRI provides a consistent control-function approach (Terza et al., 2008). In the first stage, each potentially endogenous regressor (AI, environmental sustainability, social sustainability) is modelled as a function of exogenous instruments and controls. Instruments include legal constraints, perceived regulatory barriers and digital infrastructure variables that are plausibly related to the propensity to adopt AI or sustainability practices but are not directly linked to social innovation outcomes. For AI we estimate a weighted logit with cloud computing, big-data use and digital infrastructure as predictors; for environmental and social sustainability we estimate weighted linear regressions on institutional support and legal/infrastructural variables. In the second stage, the residuals from these first-stage models are added to the main social-innovation logit alongside the original regressors. Under standard assumptions, a significant residual term signals endogeneity, while an insignificant residual indicates that the corresponding regressor behaves as exogenous.

Third, to assess sensitivity to unobserved confounding, we implement the Oster (2019) δ-method. This method compares the coefficient and R^2 from a “controlled” specification (with the full set of covariates) to those from a parsimonious specification with only the variable of interest and minimal controls. Assuming that selection on unobserved factors is proportional to selection on observables and specifying an upper bound for the attainable R^2 (we set $R_{\max} = 0.8$, a conservative value for cross-sectional survey data), Oster's δ statistic indicates how strong selection on unobservables would need to be, relative to observables, to shrink the estimated effect to zero. Large δ values imply that substantial unobserved selection would be required to overturn the results. We compute δ for AI adoption, environmental sustainability and social sustainability.

Fourth, we assess overall model performance using two complementary predictive diagnostics: the Brier score and the ROC/AUC framework. The Brier score (Brier, 1950; Murphy, 1973) measures the mean squared distance between predicted probabilities and observed binary outcomes, thereby evaluating the model's calibration. A lower score indicates better probabilistic accuracy. In contrast, the ROC curve and the Area Under the Curve (AUC) assess discrimination, that is, the model's ability to rank innovators above non-innovators (Hanelt et al., 2021; Fawcett, 2006). We additionally conduct a 70/30 train–test split to evaluate out-of-sample discrimination and guard against overfitting.

Because the environmental and social sustainability indices are constructed from multi-item checklists, we further examine the reliability and validity of these measures. To evaluate internal consistency, we compute Cronbach's alpha (Cronbach, 1951), recognising that for short, formative-like or behavioural indices, values slightly below the conventional 0.70 threshold can still be acceptable (Cortina, 1993; Schmitt, 1996). To assess convergent validity, we apply Principal Components Analysis (PCA) and polychoric factor analysis, which is appropriate for dichotomous items (Flora and Curran, 2004). Evidence of a dominant first component and strong factor loadings indicates that each index reflects a coherent underlying dimension. Finally, to establish discriminant validity between environmental and social sustainability, we examine polychoric cross-construct correlations, compute the Heterotrait–Monotrait (HTMT) ratio (Henseler et al., 2015), and evaluate the correlation between the composite indices. HTMT values below 0.85 and comparatively lower cross-construct correlations support the interpretation of the two indices as distinct constructs.

5. Analysis and results

To test Hypotheses H1–H3, we estimate a sequence of weighted logistic regression models with standard errors clustered at the country level (Tables 3 and 4). Column (1) of Table 3 presents a baseline model including only controls, while Columns (2)–(4) add each focal predictor separately. Column (5) reports the full model including AI, environmental sustainability, and social sustainability jointly.

As shown in Table 3, Column (2), the coefficient for AI adoption is small and statistically insignificant ($\beta = 0.081$, $p > 0.10$). The effect remains insignificant when environmental and social sustainability are included in the model (Column 5). Average marginal effects (AMEs) computed from the full model confirm that changes in AI adoption are not associated with statistically significant differences in the probability of developing social innovation (see Table 4). Thus, H1 is not supported.

Environmental sustainability shows a consistent and robust effect across all model specifications. When entered alone (Table 3, Column 3), the coefficient is positive and statistically significant ($\beta = 0.363$, $p < 0.001$). The effect remains significant when all predictors are included in the model (Column 5), where $\beta = 0.236$ ($p < 0.001$). AMEs from the full model show that a one-unit increase in environmental sustainability

Table 3
Main logistic regression.

	(1)	(2)	(3)	(4)	(5)
	Social Innovation	Social Innovation	Social Innovation	Social Innovation	Social Innovation
Size	0.004 (0.044)	0.004 (0.045)	−0.002 (0.038)	−0.041 (0.036)	−0.035 (0.035)
Level of Digitalisation	0.415*** (0.026)	0.409*** (0.027)	0.303*** (0.023)	0.265*** (0.022)	0.240*** (0.023)
Ecosystem Support	0.061*** (0.015)	0.061*** (0.015)	0.058*** (0.014)	0.057*** (0.013)	0.056*** (0.014)
Ease of Collaboration	−0.009 (0.070)	−0.009 (0.070)	−0.017 (0.068)	−0.025 (0.068)	−0.026 (0.068)
Access to Skills	−0.099 (0.093)	−0.099 (0.093)	−0.142* (0.082)	−0.129* (0.078)	−0.140* (0.076)
Year	−0.000 (0.002)	−0.000 (0.002)	0.002 (0.002)	0.001 (0.001)	0.002 (0.001)
AI		0.081 (0.116)	0.079 (0.115)	0.015 (0.113)	0.025 (0.114)
Environmental Sustainability			0.363*** (0.039)		0.184*** (0.032)
Social Sustainability				0.473*** (0.040)	0.383*** (0.038)
AI * Environmental Sustainability					
AI * Social Sustainability					
Environmental Sustainability * Social Sustainability					
AI * Environmental Sustainability * Social Sustainability					
Constant	−1.539 (3.478)	−1.476 (3.481)	−7.063** (3.194)	−5.571* (2.848)	−7.597*** (2.942)
Observations	11,838	11,838	11,838	11,838	11,838
Log likelihood	−5259.715	−5259.334	−5079.476	−4971.114	−4935.841
Nagelkerke R-sq.	0.047	0.047	0.080	0.100	0.106

Note: All specifications are estimated with a logistic regression using sampling weights and standard errors clustered at the country level.

Table 4
Average marginal effects from main logistic specification.

	(1)	(2)	(3)	(4)	(5)
	Social Innovation	Social Innovation	Social Innovation	Social Innovation	Social Innovation
Size	0.001 (0.006)	0.000 (0.006)	−0.000 (0.005)	−0.005 (0.005)	−0.004 (0.004)
Level of Digitalisation	0.055*** (0.004)	0.054*** (0.004)	0.039*** (0.003)	0.033*** (0.003)	0.030*** (0.003)
Ecosystem Support	0.008*** (0.002)	0.008*** (0.002)	0.007*** (0.002)	0.007*** (0.002)	0.007*** (0.002)
Ease of Collaboration	−0.001 (0.009)	−0.001 (0.009)	−0.002 (0.009)	−0.003 (0.009)	−0.003 (0.008)
Access to Skills	−0.013 (0.012)	−0.013 (0.012)	−0.018* (0.010)	−0.016* (0.010)	−0.017* (0.009)
Year	−0.000 (0.000)	−0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
AI		0.011 (0.016)	0.010 (0.015)	0.002 (0.014)	0.003 (0.014)
Environmental Sustainability			0.046*** (0.005)		0.023*** (0.004)
Social Sustainability				0.059*** (0.005)	0.048*** (0.005)
Observations	11,838	11,838	11,838	11,838	11,838

increases the probability of social innovation by approximately 4.7 percentage points, holding all else constant (Table 4, column 3). Thus, Hypothesis H2 is supported.

When entered individually (Table 3, Column 4), social sustainability is strongly associated with social innovation ($\beta = 0.473$, $p < 0.001$). The effect is virtually unchanged when AI and environmental sustainability are added (Column 5), where $\beta = 0.433$ ($p < 0.001$). AMEs indicate that a one-unit increase in social sustainability raises the probability of social innovation by 5.9 percentage points (see Table 4, Column 4). Note that for the full specification model (column 5 in Tables 3 and 4), the AMEs of social sustainability are twice the AMEs of environmental sustainability (0.023 vs 0.048). Thus, Hypothesis H3 is supported.

Table 5
Logistic regression with detailed interactions.

	(1)	(2)	(3)	(4)	(5)
	Social Innovation	Social Innovation	Social Innovation	Social Innovation	Social Innovation
Size	−0.035 (0.035)	−0.035 (0.035)	−0.035 (0.035)	−0.035 (0.035)	−0.035 (0.035)
Level of Digitalisation	0.240*** (0.023)	0.240*** (0.023)	0.240*** (0.023)	0.240*** (0.023)	0.238*** (0.023)
Ecosystem Support	0.056*** (0.014)	0.056*** (0.014)	0.056*** (0.014)	0.056*** (0.014)	0.055*** (0.014)
Ease of Collaboration	−0.026 (0.068)	−0.026 (0.068)	−0.026 (0.068)	−0.026 (0.068)	−0.026 (0.067)
Access to Skills	−0.140* (0.076)	−0.139* (0.076)	−0.140* (0.077)	−0.142* (0.076)	−0.141* (0.077)
Year	0.002 (0.001)	0.002 (0.001)	0.002 (0.001)	0.002 (0.001)	0.002 (0.001)
AI	0.025 (0.114)	−0.054 (0.258)	0.075 (0.347)	0.027 (0.113)	0.940* (0.535)
Environmental Sustainability	0.184*** (0.032)	0.182*** (0.032)	0.184*** (0.032)	0.209*** (0.057)	0.236*** (0.057)
Social Sustainability	0.383*** (0.038)	0.383*** (0.038)	0.384*** (0.040)	0.404*** (0.055)	0.433*** (0.056)
AI * Environmental Sustainability		0.029 (0.083)			−0.461** (0.220)
AI * Social Sustainability			−0.017 (0.109)		−0.422** (0.191)
Environmental Sustainability * Social Sustainability				−0.010 (0.018)	−0.023 (0.018)
AI * Environmental Sustainability * Social Sustainability					0.184** (0.076)
Constant	−7.597*** (2.942)	−7.606** (2.955)	−7.591** (2.949)	−7.639*** (2.931)	−7.786*** (2.981)
Observations	11,838	11,838	11,838	11,838	11,838
Log likelihood	−4935.841	−4935.755	−4935.820	−4935.632	−4931.102
Nagelkerke R-sq.	0.106	0.106	0.106	0.106	0.107

Note: All specifications are estimated with a logistic regression using sampling weights and standard errors clustered at the country level.

To examine potential synergies, we estimate two-way and three-way interaction models (Tables 5 and 6). These allow us to evaluate whether AI amplifies the effect of environmental or social sustainability practices, and whether all three dimensions jointly produce supermodular gains consistent with H4. The two-way interaction terms are shown in Table 5, Columns 2, 3 and 4, and Figures, 2, 3, 4 and 5. All of them are small and statistically insignificant (AI × Environmental sustainability: $\beta = 0.029$, $p > 0.10$; AI × Social sustainability: $\beta = -0.017$, $p > 0.10$; Environmental × Social sustainability: $\beta = -0.010$, $p > 0.10$). The three-way term AI × Environmental sustainability × Social sustainability is positive and statistically significant ($\beta = 0.184$, $p < 0.05$) (Table 5, Column 5). This indicates that AI creates complementarities only when environmental and social sustainability are simultaneously high. To formally test supermodularity, we compute the Milgrom and Roberts (1990) difference-in-differences contrast ($\Delta = 0.0889$, $z = 2.95$, $p = 0.003$) (Table 6). The results provide statistical evidence that when both sustainability dimensions are low or moderate, AI makes little difference, but when both sustainability dimensions are high, AI significantly increases the probability of social innovation. Thus, Hypothesis H4 is supported.

Tables 7 and 8 reports results separately for manufacturing and services, respectively. Some key patterns are consistent across sectors: environmental and social sustainability remain significant predictors in both samples, with social sustainability having a bigger impact than environmental sustainability; AI adoption remains insignificant as a standalone predictor. Interaction patterns are directionally similar, though three-way complementarities are only significant for the services sector.

5.1. Robustness checks

We conducted several robustness analyses to assess whether our findings withstand concerns related to common-method variance, endogeneity, unobserved confounding, model predictive performance, and the reliability and validity of the sustainability indices. The detailed results are reported in Tables 9–11 and the Appendix (Tables A2–A6).

To assess potential common-method bias, we re-estimated the main logistic models including the marker variable “Payment delays” (Table 9). Across all specifications, the marker coefficient is small and statistically insignificant (Table 9, column 2: $\beta = 0.010$, SE = 0.056; column 4: $\beta = 0.007$, SE = 0.057). Importantly, the coefficients for AI, environmental sustainability, and social sustainability remain unchanged in magnitude and significance when the marker is included (compare columns 1 and 2, and 3 and 4). These results indicate that common-method variance does not materially affect the main relationships.

We estimated 2SRI models for AI adoption, environmental sustainability, and social sustainability (Table 10). In the second-stage logit (columns 4–5), the residual terms for AI, environmental sustainability, and social sustainability are all statistically insignificant, indicating no detectable endogeneity. The key interaction terms remain significant and directionally consistent with the baseline estimates, including the positive three-way complementarity term ($\beta = 0.185$, $p < 0.10$). Thus, the main results do not appear to be driven by simultaneity or omitted-variable bias.

Model calibration assessed via the Brier score yields a value of 0.131, substantially lower than the 0.25 value associated with uninformed predictions, indicating good probabilistic accuracy. Discriminatory performance evaluated using ROC/AUC confirms good predictive capacity. The ROC output shows that AUC = 0.7412, Std. error = 0.0122 and 95 % CI: [0.7173, 0.7652] with 2463 observations in test sample. An AUC of 0.741 indicates good discriminatory performance, meaning the model correctly ranks an innovator above a non-innovator approximately 74 % of the time. This level of discrimination is substantially better than random guessing (AUC = 0.50) and comfortably within the accepted range for well-performing social science classification models (typically 0.70–0.80).

Internal consistency was evaluated using Cronbach's alpha. The environmental sustainability index shows an alpha of 0.685, slightly below the conventional 0.70 threshold but acceptable for short, heterogeneous behavioural indices (Schmitt, 1996; Cortina, 1993), particularly when indicators represent diverse sustainability practices rather than reflective manifestations of a single latent trait. The social sustainability index demonstrates stronger internal consistency ($\alpha = 0.723$). Item–total and item–rest correlations indicate robust internal coherence for both indices (environmental: 0.65–0.78; social: 0.67–0.80), and the “alpha-if-item-deleted” values do not improve upon item removal, confirming that all items contribute meaningfully to their respective scales (Tables A2–A3).

Second, we assess convergent validity using PCA and polychoric factor analysis. For each index, PCA identifies a strong single underlying component. For the environmental sustainability index the eigenvalue for Component 1 is 2.06 and the variance explained 51.5 %. For the social sustainability index the eigenvalue for Component 1 is 2.19 and the variance explained 54.7 %. We also find that all items load positively and substantially on the first component (Tables A2–A3). Moreover, to account for dichotomous response formats, we estimated single-factor models using the polychoric correlation matrix. Our results confirm stronger unidimensionality. For the environmental sustainability index, the eigenvalue is 2.62 and the variance explained 65.5 % with loadings between 0.75 and 0.88. For the social sustainability index eigenvalue = 2.89, variance explained = 72.2 %, loadings = 0.81–0.90 (Tables A4–A5).

Table A6 shows the polychoric correlation matrix. The mean within-environment item correlation is 0.54, the mean within-social item correlation is 0.63, and the mean cross-construct correlation is 0.46. The lower cross-block correlations indicate that items cluster naturally within their respective conceptual domains. Using the polychoric correlations, we obtain a HTMT statistic of 0.799, below the conservative threshold of 0.85, supporting that that environmental and social

Table 6
Average marginal effects from logistic interactions models.

	(1)	(2)	(3)	(4)	(5)
	Social Innovation	Social Innovation	Social Innovation	Social Innovation	Social Innovation
Size	−0.004 (0.004)	−0.004 (0.004)	−0.004 (0.004)	−0.004 (0.004)	−0.004 (0.004)
Level of Digitalisation	0.030*** (0.003)	0.030*** (0.003)	0.030*** (0.003)	0.030*** (0.003)	0.030*** (0.003)
Ecosystem Support	0.007*** (0.002)	0.007*** (0.002)	0.007*** (0.002)	0.007*** (0.002)	0.007*** (0.002)
Ease of Collaboration	−0.003 (0.008)	−0.003 (0.008)	−0.003 (0.008)	−0.003 (0.008)	−0.003 (0.008)
Access to Skills	−0.017* (0.009)	−0.017* (0.009)	−0.017* (0.009)	−0.018* (0.009)	−0.017* (0.009)
Year	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
AI	0.003 (0.014)	0.002 (0.015)	0.004 (0.016)	0.003 (0.014)	0.009 (0.019)
Environmental Sustainability	0.023*** (0.004)	0.023*** (0.004)	0.023*** (0.004)	0.023*** (0.004)	0.023*** (0.004)
Social Sustainability	0.048*** (0.005)	0.048*** (0.005)	0.048*** (0.005)	0.047*** (0.005)	0.048*** (0.004)
Observations	11,838	11,838	11,838	11,838	11,838

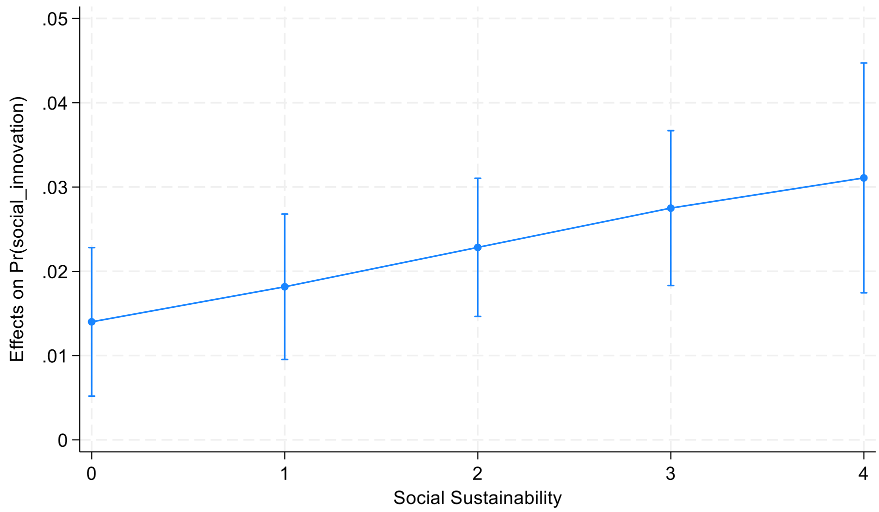

Fig. 2. Average marginal effects of Environmental Sustainability with 95 % confidence intervals.

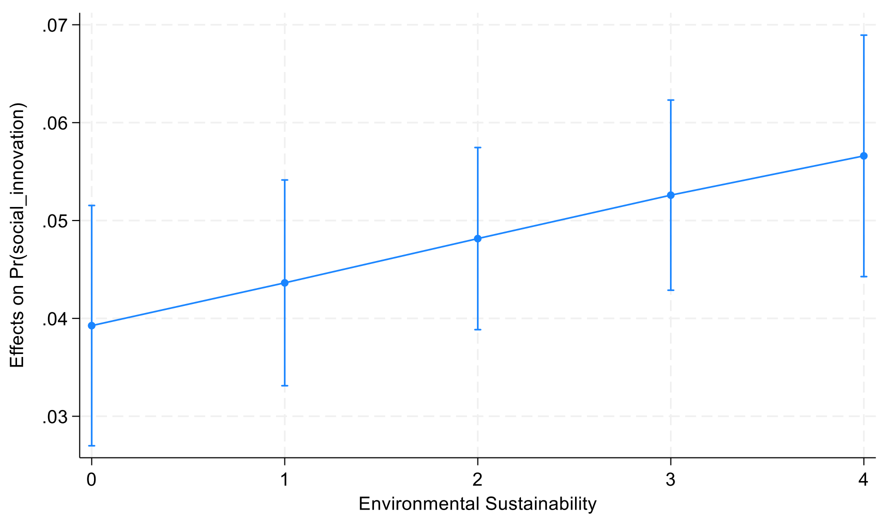

Fig. 3. Average marginal effects of Social Sustainability with 95 % confidence intervals.

sustainability reflect distinct constructs, even though they are moderately related. Finally, the simple correlation between the two composite indices is extremely small, 0.007, providing additional evidence that the indices are not collinear and capture separate dimensions of sustainability practices.

Oster bounds are presented in Table A7. For social sustainability, the estimated δ is 0.144, indicating that selection on unobservables would need to be 14 % as strong as selection on observables to explain away the effect. Similarly, environmental sustainability yields a δ of 0.131, suggesting that omitted-variable bias would have to operate at 13 % of the strength of the observed controls to eliminate the estimated coefficient. While these δ values fall below the conventional benchmark of $\delta > 1$ (which would imply very strong robustness), they nonetheless indicate that moderate levels of unobserved selection would be required to nullify the observed positive effects. By contrast, AI adoption shows a δ of 0.013, reflecting the fact that the AI coefficient is statistically insignificant in the baseline model. The very small δ value indicates that even minimal unobserved confounding would be sufficient to reduce the AI effect to zero, which is fully consistent with the conclusion that AI does not have a direct main effect on social innovation in SMEs. As several methodological studies have emphasized (Oster, 2019; Cinelli and Hazlett, 2020; Gelman and Hill, 2007), cross-sectional survey data typically exhibit low R^2 values, because only a limited share of variance can be explained by observable covariates. Since Oster's δ statistic depends on the attainable R^2 range, δ values in cross-sectional social science settings are naturally small.

6. Discussion

Our findings show that AI adoption does not exert a significant direct effect on the development of social innovation in SMEs. This contrasts with much of the emerging literature portraying AI as an important enabler of sustainability-oriented or socially oriented innovation (Ardito, 2023; Wang et al., 2023, 2024). Rather than contradicting these views, our results suggest that AI's influence unfolds in more indirect and capability-dependent ways than previously assumed.

The non-significant coefficient indicates that AI operates as a foundational capability. It does not function as a stand-alone driver of socially innovative outcomes. AI improves operational efficiency and resource utilization (Adams et al., 2017; Zhang et al., 2025), but these

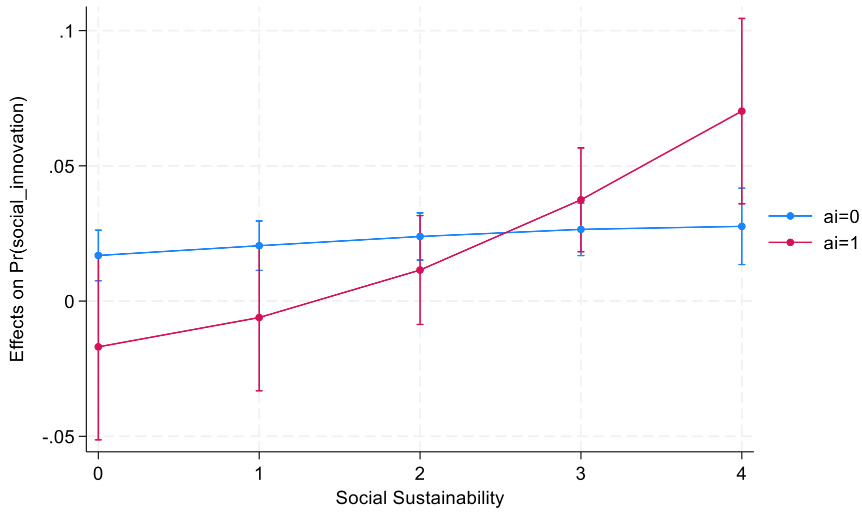

Fig. 4. Effect of AI on the average marginal effects of Environmental Sustainability with 95 % confidence intervals.

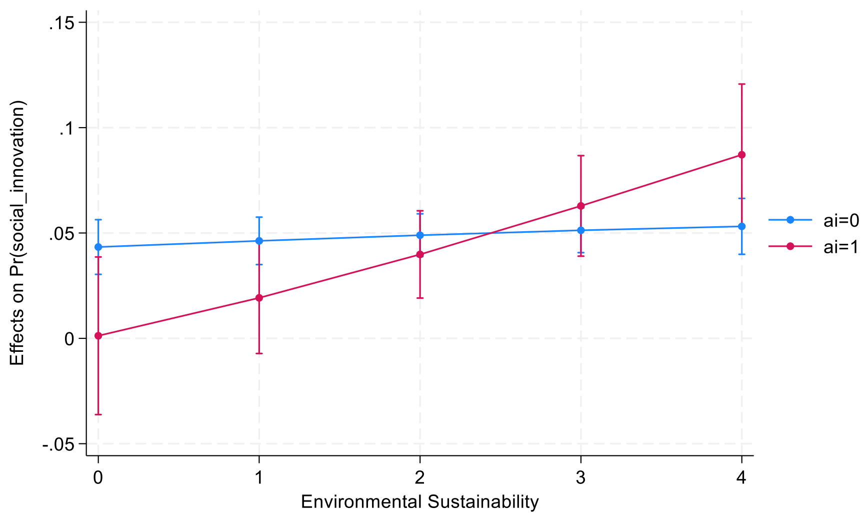

Fig. 5. Effect of AI on average marginal effects of Social Sustainability with 95 % confidence intervals.

improvements do not automatically translate into social innovation unless combined with complementary sustainability-oriented or relational capabilities. AI also expands firms' diagnostic and sensing capacities: machine-learning and analytical tools enhance SMEs' ability to interpret dispersed social data, identify unmet community needs, and detect emerging vulnerabilities (Chen et al., 2018; Garcia and Lee, 2018; Chhillar and Aguilera, 2022; Erdiaw-Kwasie and Abunyewah, 2024). Yet these enhanced sensing routines do not, by themselves, determine whether firms act upon such insights in socially innovative ways; this depends on organisational culture, stakeholder relationships, and sustainability-related capabilities (Gupta, 2024; Adams et al., 2017). Consequently, AI strengthens the resource base on which social innovation can be built but does not represent the mechanism through which social innovation is directly produced. Moreover, the absence of a direct effect is also consistent with the pressures SMEs face. Many small firms adopt AI in response to coercive, normative, and mimetic pressures to appear modern, transparent, or technologically competent (Dubey, 2025). Legitimacy-driven adoption, however, often results in symbolic or partial implementation, which rarely produces substantive innovation outcomes. AI adoption therefore may satisfy institutional expectations without yet reshaping organisational routines sufficiently to yield social innovation. Moreover, the absence of a direct effect might also be due to the empirical approach. In particular, our measure of AI adoption is binary and does not capture variation in intensity or type of AI use, which likely attenuates observable relationships. The survey lacks sector-specific granularity. It was conducted in early 2020, when many SMEs were still in the early stages of experimenting with AI tools, and before more mature or strategically embedded AI capabilities had developed, reducing the likelihood of detecting strong innovation effects.

In reference to Hypothesis 2, concerning the effect of environmental sustainability on the development of social innovation in SMEs, we observe a positive effect, indicating that prioritizing environmental sustainability contributes not only to the conservation of natural resources and pollution reduction but also catalyzes the development of innovative solutions addressing both environmental and social challenges (Graham, 2020; Bansal and Song, 2017; Schaltegger and Wagner, 2011; Ciliberti et al., 2008). Our findings reinforce prior research, which demonstrates how environmental activities encourage SMEs to reconsider their production processes, supply chains, and product designs

Table 7
Logistic for the manufacturing industry.

	(1)	(2)	(3)	(4)	(5)	(6)
	Social Innovation	Social Innovation	Social Innovation	Social Innovation	Social Innovation	Social Innovation
Size	−0.060 (0.066)	−0.061 (0.066)	−0.061 (0.060)	−0.083 (0.064)	−0.077 (0.060)	−0.081 (0.061)
Level of Digitalisation	0.388*** (0.056)	0.381*** (0.059)	0.264*** (0.049)	0.211*** (0.063)	0.182*** (0.059)	0.179*** (0.059)
Ecosystem Support	−0.010 (0.041)	−0.010 (0.041)	−0.017 (0.041)	−0.003 (0.040)	−0.007 (0.041)	−0.006 (0.041)
Ease of Collaboration	−0.277 (0.209)	−0.275 (0.208)	−0.309 (0.201)	−0.310 (0.207)	−0.327 (0.203)	−0.333* (0.200)
Access to Skills	0.176 (0.190)	0.176 (0.190)	0.149 (0.193)	0.204 (0.180)	0.189 (0.185)	0.191 (0.189)
Year	0.004 (0.005)	0.004 (0.005)	0.007 (0.005)	0.005 (0.004)	0.006 (0.005)	0.007 (0.005)
AI		0.126 (0.235)	0.109 (0.222)	0.031 (0.249)	0.038 (0.235)	0.214 (1.215)
Environmental Sustainability			0.371*** (0.061)		0.199*** (0.060)	0.217* (0.114)
Social Sustainability				0.481*** (0.079)	0.390*** (0.087)	0.405** (0.165)
AI * Environmental Sustainability						−0.398 (0.581)
AI * Social Sustainability						−0.185 (0.554)
Environmental Sustainability * Social Sustainability						−0.011 (0.053)
AI * Environmental Sustainability * Social Sustainability						0.166 (0.204)
Constant	−9.621 (9.587)	−9.591 (9.569)	−15.602 (9.627)	−12.995 (8.822)	−15.529* (9.049)	−15.809* (8.974)
Observations	2204	2204	2204	2204	2204	2204
Log likelihood	−505.404	−505.316	−488.250	−478.246	−474.284	−473.713
Nagelkerke R-sq.	0.046	0.046	0.079	0.098	0.105	0.106

Note: All specifications are estimated with a logistic regression using sampling weights and standard errors clustered at the country level.

Table 8
Logistic regression for the services industry.

	(1)	(2)	(3)	(4)	(5)	(6)
	Social Innovation	Social Innovation	Social Innovation	Social Innovation	Social Innovation	Social Innovation
Size	0.034 (0.052)	0.034 (0.052)	0.029 (0.044)	−0.014 (0.042)	−0.007 (0.040)	−0.006 (0.040)
Level of Digitalisation	0.397*** (0.028)	0.394*** (0.030)	0.288*** (0.027)	0.247*** (0.028)	0.222*** (0.028)	0.220*** (0.028)
Ecosystem Support	0.062*** (0.016)	0.062*** (0.016)	0.059*** (0.014)	0.055*** (0.013)	0.055*** (0.014)	0.054*** (0.013)
Ease of Collaboration	0.041 (0.075)	0.041 (0.075)	0.038 (0.071)	0.037 (0.071)	0.036 (0.070)	0.039 (0.070)
Access to Skills	−0.102 (0.088)	−0.102 (0.088)	−0.143* (0.079)	−0.149* (0.078)	−0.156** (0.077)	−0.156** (0.076)
Year	−0.001 (0.002)	−0.001 (0.002)	0.002 (0.002)	0.001 (0.001)	0.002 (0.001)	0.002 (0.001)
AI		0.048 (0.124)	0.067 (0.121)	0.007 (0.121)	0.024 (0.120)	1.082* (0.561)
Environmental Sustainability			0.365*** (0.037)		0.188*** (0.031)	0.239*** (0.065)
Social Sustainability				0.476*** (0.042)	0.385*** (0.042)	0.435*** (0.066)
AI * Environmental Sustainability						−0.554** (0.229)
AI * Social Sustainability						−0.497** (0.197)
Environmental Sustainability * Social Sustainability						−0.023 (0.022)
AI * Environmental Sustainability * Social Sustainability						0.224*** (0.075)
Constant	−1.118 (3.352)	−1.071 (3.376)	−6.362** (3.108)	−4.811* (2.736)	−6.849** (2.830)	−7.079** (2.907)
Observations	8240	8240	8240	8240	8240	8240
Log likelihood	−4202.558	−4202.447	−4055.172	−3967.363	−3937.561	−3931.761
Nagelkerke R-sq.	0.044	0.044	0.078	0.098	0.105	0.106

Note: All specifications are estimated with a logistic regression using sampling weights and standard errors clustered at the country level.

with sustainability in mind (Adjei-Bamfo et al., 2023; De Marchi et al., 2022; González-Benito et al., 2009; Russo and Perrini, 2010; Christmann, 2000; Jones and Smith, 2020; Valliere and Peterson, 2009). Moreover, our results extend previous findings, indicating that environmental activities often necessitate SMEs to engage with a broader set of stakeholders, including environmental groups, regulatory bodies, and the community at large (Hafeez et al., 2024; Cohen et al., 2013; Russo and Perrini, 2010; Margolis and Walsh, 2003; King and Lenox, 2001; Aza-Mengoa et al., 2025). Additionally, our findings highlight the significance of environmental sustainability initiatives in resilient long-term cost savings by promoting efficient resource and energy utilization, reducing waste, and mitigating environmental risks (Porter and van der Linde, 1995). These cost savings can be redirected towards social innovation projects, thereby encouraging SMEs' ability to make meaningful contributions to social welfare (Vos et al., 2019).

Regarding Hypothesis 3, our findings demonstrate that the adoption of social sustainability by SMEs has a significant impact on social innovation. Consistent with the findings of Ferraro and Gao (2018) and

Table 9
Main logistic regression including a marker as a regressor.

	(1)	(2)	(3)	(4)
	Social Innovation	Social Innovation	Social Innovation	Social Innovation
Size	−0.035	−0.035	−0.035	−0.035
	(0.035)	(0.035)	(0.035)	(0.035)
Level of Digitalisation	0.240***	0.240***	0.238***	0.238***
	(0.023)	(0.023)	(0.023)	(0.023)
Ecosystem Support	0.056***	0.056***	0.055***	0.055***
	(0.014)	(0.015)	(0.014)	(0.014)
Ease of Collaboration	−0.026	−0.027	−0.026	−0.026
	(0.068)	(0.068)	(0.067)	(0.067)
Access to Skills	−0.140*	−0.140*	−0.141*	−0.141*
	(0.076)	(0.076)	(0.077)	(0.077)
Year	0.002	0.002	0.002	0.002
	(0.001)	(0.001)	(0.001)	(0.001)
AI	0.025	0.025	0.940*	0.941*
	(0.114)	(0.114)	(0.535)	(0.535)
Environmental Sustainability	0.184***	0.184***	0.236***	0.236***
	(0.032)	(0.032)	(0.057)	(0.057)
Social Sustainability	0.383***	0.383***	0.433***	0.433***
	(0.038)	(0.038)	(0.056)	(0.056)
Marker		*0.010*		*0.007*
		(0.056)		*(0.057)*
AI * Environmental Sustainability			−0.461**	−0.461**
			(0.220)	(0.220)
AI * Social Sustainability			−0.422**	−0.422**
			(0.191)	(0.191)
Environmental Sustainability * Social Sustainability			−0.023	−0.023
			(0.018)	(0.018)
AI * Environmental Sustainability * Social Sustainability			0.184**	0.184**
			(0.076)	(0.076)
Constant	−7.597***	−7.583**	−7.786***	−7.776***
	(2.942)	(2.947)	(2.981)	(2.986)
Observations	11,838	11,838	11,838	11,838
Log likelihood	−4935.841	−4935.823	−4931.102	−4931.094
Nagelkerke R-sq.	0.106	0.106	0.107	0.107

Note: All specifications are estimated with a logistic regression using sampling weights and standard errors clustered at the country level. Our marker was defined as a binary variable equal to 1 if the company declared payment delays as a barrier to the organisation.

Schaltegger and Burritt (2018), social sustainability initiatives prompt SMEs to rethink their operations, supply chains, and product offerings holistically, considering both environmental impact and social responsibility. This approach often leads SMEs to focus on sustainable sourcing and develop products that are environmentally friendly and socially beneficial, as noted by Sudsawasd et al. (2018) and Hutchins and Sutherland (2008). Furthermore, our results reinforce prior research indicating that integrating social sustainability into their operations can enhance the competitive advantage and market positioning of SMEs, as evidenced by the works of Graafland et al. (2020), Barbieri et al. (2020), and Schwartz et al. (2019). Additionally, our findings highlight how engaging in social sustainability practices necessitates collaboration with various stakeholders, including local communities, NGOs, and government agencies (Cohen and Winn, 2007; Longoni et al., 2018; Graves and Sarkis, 2018; Carberry et al., 2019). Moreover, implementing sustainability activities enables SMEs to anticipate and adapt to regulatory changes and societal shifts toward sustainability, as suggested by Dangelico and Pujari (2010) and Boons and Lüdeke-Freund (2013).

The stronger effects of environmental and social sustainability can also be understood through the dual theoretical lens. Under RBT, these practices represent bundles of tangible and intangible resources—reputational assets, stakeholder relationships, employee commitment—that directly contribute to firms' ability to innovate. Under institutional theory, sustainability has become institutionalized as a normative and regulatory expectation in Europe, meaning that SMEs that adopt these practices not only secure legitimacy but also align themselves with societal priorities. When combined, these resource-based and institutional dimensions explain why sustainability—especially social sustainability—emerges as the most consistent predictor of social innovation.

In reference to Hypothesis 4, our findings provide evidence of synergistic complementarities among AI, environmental sustainability, and social sustainability in shaping SMEs' social innovation. Our results suggests that the three practices act as mutually reinforcing capabilities, but only after a certain capability threshold is reached. Environmental sustainability provides SMEs with routines for eco-efficiency, pollution prevention, and process optimisation (Hart, 1995; Aragón-Correa and Sharma, 2003). Social sustainability contributes relational capital, trust, employee engagement, and knowledge-sharing structures (Aguinis and Glavas, 2012; Barrena-Martínez et al., 2019). AI adds advanced sensing, analytical, and coordination capabilities that enhance both exploitative and exploratory learning (Teece, 2007; Sjödin et al., 2023). When these three domains are simultaneously strong, SMEs can orchestrate them into a resource bundle that expands problem-sensing, improves stakeholder alignment, and accelerates the recombination of knowledge into socially innovative solutions. Synergy therefore arises not from the isolated effect of any single capability, but from their configuration into a coherent capability system (Teece et al., 1997). Moreover, the synergy also reflects the convergence of multiple institutional pressures. Environmental sustainability is shaped strongly by coercive forces (e.g. EU environmental directives), while social sustainability is shaped by normative pressures related to fairness, inclusion, community expectations, and employee welfare (Schaltegger and Wagner, 2011; Dempsey et al., 2011). AI adoption is driven primarily by mimetic and competitive pressures linked to digitalisation benchmarks, transparency expectations, and industry modernisation trends (Dubey, 2025). Our results suggest that complementarities emerge only when SMEs internalise these pressures in a consistent and aligned manner. Firms that merely comply symbolically with sustainability or digitalisation do not experience synergy; instead, synergy appears when firms meaningfully integrate sustainability practices and digital technologies, thereby achieving a high degree of institutional alignment.

The marginal-effects patterns also support this interpretation. When environmental and social sustainability are both low or moderate, the firm lacks the capability infrastructure and institutional alignment necessary for AI to enhance social innovation. However, when sustainability practices are both strong, AI amplifies their effects by enabling more accurate environmental performance monitoring, improving resource forecasting, supporting stakeholder engagement, and facilitating transparent reporting of social outcomes (Johnson and White, 2021; Melville et al., 2009).

For practitioners, the findings imply that SMEs should treat AI adoption and sustainability practices as complementary rather than isolated strategies. In practice, this means investing not only in AI tools but also in the organizational capabilities (e.g. skilled employees, data management processes, and stakeholder engagement mechanisms) that allow AI to support sustainability goals. Environmental practices should be approached not simply as compliance with regulation but as opportunities for co-creation with supply chain partners, customers, and communities. Social sustainability should be prioritized, as it generates the strongest innovation outcomes: inclusive workplace practices, participatory decision-making, and fair employment policies foster employee creativity and strengthen trust with stakeholders. However, SMEs also face barriers such as resource scarcity, lack of technical expertise, and uncertainty about returns. Policymakers and business associations can play a crucial enabling role by providing subsidies, technical training, and collaborative platforms that lower the costs and risks of integrating AI with sustainability practices.

Finally, our findings demonstrate differential impacts among the

Table 10
Two-stage residual inclusion (2SRI).

	(1)	(2)	(3)	(4)	(5)
	AI	Environmental Sustainability	Social Sustainability	Social Innovation	Social Innovation
Digitalisation Plan	0.127*** (0.039)				
Infrastructure	0.334* (0.178)	0.137** (0.050)	0.108* (0.059)		
Legal Environment	0.110 (0.113)	−0.114** (0.046)	−0.141** (0.060)		
Cluster membership		0.594*** (0.105)	0.724*** (0.093)		
Size	0.021 (0.045)	0.005 (0.031)	0.105*** (0.033)	−0.222 (0.213)	−0.223 (0.212)
Level of Digitalisation	0.871*** (0.036)	0.321*** (0.020)	0.366*** (0.025)	0.184** (0.076)	0.180** (0.077)
Ecosystem Support	−0.025 (0.026)	0.021 (0.017)	0.019 (0.020)	0.067*** (0.019)	0.067*** (0.018)
Ease of Collaboration	0.021 (0.118)	0.021 (0.041)	0.052 (0.047)	−0.079 (0.078)	−0.079 (0.078)
Access to Skills	0.083 (0.118)	0.122* (0.065)	0.078 (0.076)	−0.028 (0.171)	−0.029 (0.168)
Year	0.004 (0.003)	−0.007*** (0.002)	−0.003 (0.002)	−0.007 (0.011)	−0.007 (0.011)
AI				0.534 (0.579)	1.484* (0.835)
Environmental Sustainability				−1.899 (2.336)	−1.857 (2.317)
Social Sustainability				2.243 (1.976)	2.310 (1.967)
AI Residual				−0.526 (0.569)	−0.529 (0.595)
Env. Sus. Residual				2.081 (2.332)	2.094 (2.319)
Social Sust. Residual				−1.863 (1.976)	−1.878 (1.966)
AI * Environmental Sustainability					−0.470** (0.223)
AI* Social Sustainability					−0.429** (0.190)
Environmental Sustainability * Social Sustainability					−0.024 (0.018)
AI* Environmental Sustainability *Social Sustainability					0.185** (0.077)
Constant	−12.993** (5.550)	14.760*** (3.002)	6.419* (3.358)	11.177 (22.501)	11.081 (22.460)
Observations	11,838	11,838	11,838	11,838	11,838
Log likelihood	−2305.966	−19892.192	−19782.720	−4933.454	−4928.641
R-sq.	0.202	0.131	0.166	0.106	0.107

Note: Specifications 1, 4 and 5 are estimated with a logistic regression and models 2 and 3 with a liner regression. All specifications employ sampling weights and standard errors clustered at the country level.

Table 11
Train–test split validation: Logistic regression estimates.

	(1)	(2)
	Social Innovation	Social Innovation
	TRAIN	**TEST**
Size	−0.013 (0.037)	−0.086 (0.064)
Level of Digitalisation	0.244*** (0.027)	0.223*** (0.044)
Ecosystem Support	0.061*** (0.017)	0.043 (0.029)
Ease of Collaboration	−0.009 (0.071)	−0.076 (0.136)
Access to Skills	−0.072 (0.091)	−0.305*** (0.094)
Year	0.003 (0.002)	0.001 (0.003)
AI	1.040* (0.628)	0.640 (0.737)
Environmental Sustainability	0.235*** (0.063)	0.239** (0.106)
Social Sustainability	−0.400* (0.222)	−0.660* (0.388)
AI * Environmental Sustainability	0.410*** (0.067)	0.491*** (0.087)
AI * Social Sustainability	−0.465** (0.222)	−0.324 (0.327)
Environmental Sustainability * Social Sustainability	−0.022 (0.023)	−0.025 (0.031)
AI * Environmental Sustainability * Social Sustainability	0.168** (0.074)	0.241* (0.134)
Constant	−8.606** (3.930)	−6.009 (6.974)
Observations	8257	3581
Wald Chi-sq	612.444	413.685
p-value	0.000	0.000
R-sq.	0.102	0.121
Log. Likelihood	−3493.753	−1430.757

Note: All specifications are estimated with a logistic regression using sampling weights and standard errors clustered at the country level. Column 1 corresponds to the training data and column 2 to the testing data.
Out-of-Sample Predictive Performance (Test Sample): Observations (test set): 3581; ROC area (AUC): 0.7403; Std. error: 0.0170; 95 % CI: [0.71398, 0.76122].

three practices. While AI shows a greater emphasis on economic aspects such as efficiency and information management, both environmental sustainability and social sustainability exert significant influences on social innovation. Consistent with the definitions provided by Murray et al. (2010) and Westley et al. (2017a,b), who characterize social innovation as the creation and application of new solutions to address social challenges and meet societal needs, our results highlight the role of social sustainability over environmental sustainability. Following Dempsey et al. (2011) and Wilkinson and Pickett (2009), who emphasize the role of social sustainability in fostering long-term well-being and equity within societies, alongside Sen (1999), who underscores the promotion of human rights and equal opportunities as essential elements of social sustainability, our findings underscore the role of social sustainability in driving social innovation. Additionally, drawing from the insights of Bullard (1993) and Wilkinson and Pickett (2009), which shed light on the interconnectedness between social sustainability and environmental justice, although environmental sustainability contributes to social innovation, its impact is relatively less pronounced compared to social sustainability. Thus, environmental sustainability has a multi-objective character, focusing on preserving natural resources and mitigating pollution but also stimulating the development of innovative solutions addressing both environmental and social challenges (Bansal and Song, 2017; Schaltegger and Wagner, 2011; Ciliberti et al., 2008).

7. Conclusion

This paper contributes theoretically to the field of innovation theory by investigating the synergistic effects of environmental sustainability, social sustainability, and AI on social innovation within SMEs. First, we show that social sustainability is the strongest and most consistent predictor of social innovation. This highlights the centrality of human and relational capabilities (e.g. trust, inclusion, employee engagement, and stakeholder relationships) in enabling SMEs to generate socially oriented innovations. Second, environmental sustainability also positively influences social innovation, but its effect is smaller, suggesting that environmental routines provide important operational and reputational foundations, yet require complementary capabilities to translate into socially innovative outcomes. Third, while AI alone has no direct effect, our results demonstrate that AI becomes consequential when embedded within firms that already maintain high levels of both environmental and social sustainability. The positive and significant three-way interaction confirms that AI functions as a capability amplifier rather than a stand-alone driver, reinforcing the idea that digital technologies yield innovative benefits only when aligned with strong sustainability capabilities. These insights refine existing theories by showing that the value of AI depends on capability thresholds and institutional alignment, thereby advancing RBT and Institutional Theory in the context of SME social innovation.

Beyond theoretical contributions, the findings carry important managerial implications. For practitioners, social sustainability emerges as the most powerful lever for social innovation. SMEs that invest in fair labour conditions, inclusion, employee development, and stakeholder engagement build the trust, collaboration, and problem-solving capacity needed to sustain innovation. Environmental sustainability remains essential for long-term competitiveness: eco-efficiency, waste reduction, and responsible resource use generate cost savings, reputational value, and new opportunities for environmental and social solutions. AI adoption should not be approached as a purely technical upgrade. Instead, managers should integrate AI into existing sustainability routines, such as environmental monitoring, resource optimisation, and stakeholder communication, to magnify the social impact of their sustainability efforts. The results also suggest that isolated adoption of AI or sustainability practices yields limited benefits; meaningful innovation requires strategic coordination across technological and sustainability domains.

The study additionally offers policy implications, particularly relevant to European regulatory agendas. The finding that environmental and social sustainability significantly enhance social innovation supports the objectives of the EU Green Deal, the Circular Economy Action Plan, and the Sustainable SME Strategy, all of which emphasize the need for SMEs to integrate ecological responsibility and social equity into their operations. Our evidence suggests that policies that strengthen SMEs' sustainability capacities, such as subsidies for eco-innovation, training programmes for inclusive workplace practices, and support for community–SME partnerships, are likely to generate spillovers into social innovation. Moreover, because AI contributes to social innovation only when sustainability capabilities are strong, policies promoting digital transformation (e.g., through the Digital Europe Programme) should be paired with sustainability support measures rather than implemented in isolation. For policymakers, this implies that digitalisation incentives must be embedded in a broader sustainability framework to achieve maximal societal impact.

Finally, this study has limitations that offer avenues for future research. The cross-sectional design prevents causal inference, and future work could employ longitudinal or quasi-experimental methods to examine temporal dynamics between sustainability, AI, and social innovation. While this study identifies capability complementarities, the underlying organisational mechanisms (i.e. learning routines, cultural transformation, or inter-organisational collaboration) remain underexplored. Qualitative or mixed-methods studies could provide deeper insight into how SMEs translate sustainability and AI investments into innovative outcomes. Future research could also examine sector-specific pathways in more depth, as preliminary analyses indicate that complementarities may manifest differently across manufacturing and service industries. In this sense, future research could also explore alternative ways to measure AI and to understand its relationships with environmental and social sustainability, to have deeper and more meaningful understanding of the relationship between these constructs and social innovation. Qualitative research could prove a fruitful venue for this.

CRediT authorship contribution statement

Marta F. Arroyabe: Writing – original draft, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Carlos F.A. Arranz:** Writing – original draft, Methodology, Investigation, Formal analysis, Data curation, Conceptualization.

Declaration of competing interest

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

Appendix

Table A1
Variable Definitions, Type, Measurement, and Questionnaire Wording

Variable name	Type	Questionnaire wording	Measurement/Coding	Reliability
Dependent Variable				
Social Innovation	Binary	Q19: "During the past 12 months, has your enterprise introduced any of the following types of innovations? Social innovations, such as new products, services or processes that have the aim of improving society"	= 1 if "Social innovations …" selected; = 0 otherwise.	n/a
Main independent variables				
Environmental Sustainability	Cumulative index (0–4)	Q24. Environmental and social sustainability actions: "Which of the following actions, if any, is your enterprise actively taking? Recycling or reusing materials; Reducing consumption of or impact on natural resources (e.g., saving water or switching to sustainable resources); Saving energy or switching to sustainable energy sources; Developing sustainable products or services"	Sum of environmental items coded 1 if selected, 0 otherwise. Score from 0 to 4. Higher = more social sustainability actions.	Cronbach's α = 0.685
Social Sustainability	Cumulative index (0–4)	Q24. Environmental and social sustainability actions: "Which of the following actions, if any, is your enterprise actively taking? Improving working conditions of its employees; Promoting and improving diversity and equality in the workplace; Evaluating the impact of your enterprise on society; Engaging employees in the governance of the enterprise."	Sum of social items coded 1 if selected, 0 otherwise. Score from 0 to 4. Higher = more social sustainability actions.	Cronbach's α = 0.723
AI	Binary	Q23. Digital technologies adopted: "Which of the following digital technologies, if any, has your enterprise adopted to date?	= 1 if respondent selected "Artificial intelligence" Q23; = 0 otherwise.	n/a

(*continued on next page*)

Table A1 (*continued*)

Variable name	Type	Questionnaire wording	Measurement/Coding	Reliability
		Artificial intelligence, e.g. machine learning or technologies identifying objects or persons, etc."		
Control Variables				
Size	Continuous	Q2A: "How many employees, excluding the owners, does your enterprise have?"	Logarithm of the answer provided plus one.	n/a
Level of Digitalisation	Ordinal (0–6)	Q23. "Which of the following digital technologies, if any, has your enterprise adopted to date?" Cloud computing, i.e. storing and processing files or data on remote servers hosted on the internet; Robotics, i.e. robots used to automate processes for example in construction or design, etc.; Smart devices, e.g. smart sensors, smart thermostats, etc.; Big data analytics, e.g. data mining and predictive analysis; High speed infrastructure; Blockchain	Count of technologies adopted (0–6)	n/a
Ecosystem Support	Ordinal (0–8)	Q16. How would you rate your business environment in terms of: Quality of support services for businesses provided by private and public actors; Availability of support to help enterprises become more sustainable"	Sum of scores of the two items. Reverse-coded so higher values = higher rating, with 0 being very poor, and 8 being very good.	n/a
Ease of Collaboration	Binary	Q16. "How would you rate your business environment in terms of: Access to and collaboration with business partners, including other enterprises, public sector, educational institutions, research organizations, etc."	= 1 if collaboration is rated as "very good" or "fairly good"; = 0 otherwise.	n/a
Access to Skills	Binary	Q16. "How would you rate your business environment in terms of: Availability of staff with the right skills, including managerial skills."	= 1 if collaboration is rated as "very good" or "fairly good"; = 0 otherwise.	n/a
Year	Continuous	Q1: "In what year was your enterprise first registered?"	Registration year (numeric)	n/a

Table A2
Environmental Sustainability Scale Diagnostics

Item description	Item–test correlation	Item–rest correlation	Alpha if item deleted	PCA loading (Comp1)	PCA loading (Comp2)	PCA loading (Comp3)	PCA loading (Comp4)
Recycling or reusing materials	**0.688**	0.422	0.649	**0.468**	−0.533	0.691	0.138
Reducing consumption of natural resources	**0.777**	0.555	0.56	**0.552**	0.087	−0.287	−0.777
Saving energy or switching to sustainable energy	**0.744**	0.502	0.597	**0.524**	0.14	0.588	0.601
Developing sustainable products/ services	**0.654**	0.395	0.663	**0.448**	0.829	0.315	0.108

Note: Cronbach's α: 0.685, PCA (Component 1): eigenvalue = 2.061, variance explained = 51.5 %.

Table A3
Social Sustainability Scale Diagnostics

Item description	Item–test correlation	Item–rest correlation	Alpha if item deleted	PCA loading (Comp1)	PCA loading (Comp2)	PCA loading (Comp3)	PCA loading (Comp4)
Improving working conditions	**0.742**	0.523	0.655	**0.508**	−0.478	−0.428	0.575
Promoting diversity/equality	**0.796**	0.589	0.613	**0.543**	−0.128	−0.267	−0.785
Assessing societal impact	**0.668**	0.432	0.705	**0.447**	0.857	0.136	0.213
Employee engagement in governance	**0.745**	0.506	0.656	**0.496**	−0.143	0.853	0.076

Note: Cronbach's α: 0.723, PCA (Component 1): eigenvalue = 2.187, variance explained = 54.7 %.

Table A4
Environmental Sustainability Index: Convergent Validity

Panel A: Model Fit and Factor Statistics

Statistic	Value
Number of factors retained	1
Eigenvalue (Factor 1)	**2.6208**
Variance explained (Factor 1)	**65.50 %**
Total variance explained	65.50 %
LR Test (independent vs. saturated)	$\chi^2(6) = 1.8e{+}04$, $p < 0.001$

Panel B: Factor Loadings and Uniqueness

Item	Loading	Uniqueness
Recycling/reusing materials	**0.765**	0.415
Reducing natural resource use	**0.878**	0.229

(*continued on next page*)

Table A4 (*continued*)

Panel B: Factor Loadings and Uniqueness		
Item	Loading	Uniqueness
Saving or switching energy sources	**0.834**	0.306
Sustainable products/services	**0.754**	0.403

Note: Method: Polychoric factor analysis; Sample: n = 12,108; Extraction: Principal-component factors; Rotation: None (single-factor solution).

Table A5
Social Sustainability Index: Convergent Validity

Panel A: Model Fit and Factor Statistics	
Statistic	Value
Number of factors retained	1
Eigenvalue (Factor 1)	**2.8880**
Variance explained (Factor 1)	**72.2 %**
Total variance explained	72.2 %
LR Test (independent vs. saturated)	$\chi^2(6) = 2.4e{+}04$, $p < 0.001$

Panel B: Factor Loadings and Uniqueness		
Item	Loading	Uniqueness
Recycling/reusing materials	**0.872**	0.239
Reducing natural resource use	**0.894**	0.199
Saving or switching energy sources	**0.805**	0.352
Sustainable products/services	**0.823**	0.321

Note: Method: Polychoric factor analysis; Sample: n = 12,108; Extraction: Principal-component factors; Rotation: None (single-factor solution).

Table A6
Polychoric Correlation Matrix for Environmental and Social Sustainability Items

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(1) Recycling/reusing materials	1	0.567	0.497	0.434	0.408	0.473	0.425	0.404
(2) Reducing natural resource use	0.567	1	0.687	0.553	0.53	0.557	0.516	0.481
(3) Saving or switching energy sources	0.497	0.687	1	0.487	0.437	0.459	0.441	0.419
(4) Sustainable products/services	0.434	0.553	0.487	1	0.443	0.49	0.521	0.425
(5) Recycling/reusing materials	0.408	0.53	0.437	0.443	1	0.742	0.572	0.634
(6) Reducing natural resource use	0.473	0.557	0.459	0.49	0.742	1	0.645	0.634
(7) Saving or switching energy sources	0.425	0.516	0.441	0.521	0.572	0.645	1	0.54
(8) Sustainable products/services	0.404	0.481	0.419	0.425	0.634	0.634	0.54	1

Table A7
Oster (2019) δ Sensitivity Analysis.

Predictor	Controlled β	Uncontrolled β	R^2 (Crtl)	R^2 (Uncrtl)	Rmax	δ
Social sustainability	0.058***	0.07	0.088	0.071	0.8	**0.144**
Environmental sustainability	0.047***	0.059	0.073	0.049	0.8	**0.131**
AI adoption	0.025 (n.s.)	0.129	0.046	0.007	0.8	**0.013**

Data availability

The title page includes a link to the data

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