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# Twin transitions or a meeting of strangers? Unravelling the effects of AI and innovations on economic, social and environmental MSMEs sustainability

Joan Torrent-Sellens, Mihaela Enache-Zegheru *, Pilar Ficapal-Cusí

*Faculty of Economics and Business Studies and ICT Interdisciplinary Research Group (i2TIC), Universitat Oberta de Catalunya, Barcelona, Spain*

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A B S T R A C T

This research seeks to expand understanding of the twin transition -digital transformation and socio-economic and environmental sustainability-in firms by examining the impact of a specific digital technology family (artificial intelligence-based technological systems, AITS) and a comprehensive view of innovation encompassing their economic, social, and environmental dimensions. While increasing evidence highlights the influence of AITS on innovation and various economic and firm results, there is a notable gap of studies exploring the social, economic, and environmental sustainability pathways arising from the interplay between AITS usage and different types of innovation. This paper aims to address this gap. Additionally, the study investigates the moderating effects of the digital innovation strategy on the relationship between AITS and sustainability. Using a large, representative sample of 12,326 micro, small, and medium-sized enterprises (MSMEs) across 29 European Union countries in 2020, and employing structural equation modelling with partial least squares (PLS-SEM), the research identifies multiple social, economic, and environmental sustainability pathways. The results indicate that economic innovation serves as a key driver of sustainability across all dimensions, positively mediated by environmental and social innovation and the adoption of AITS. Nevertheless, is particularly relevant the finding of a substitution effect between the digital and socio-environmental transitions. For European MSMEs, the digital strategy exerts a negative moderating effect on the relationship between AITS and social and environmental sustainability. The study also uncovers other heterogeneous pathways based on firm size.

## 1. Introduction

The second digital wave positions artificial intelligence (AI) as a general-purpose technology (Crafts, 2021; Goldfarb et al., 2023) and the invention of a method to invent (Grashof & Kopka, 2023). The capacity of AI as a technological platform is driving the development and convergence of various complementary technological families, favouring the creation of AI-based technological systems (hereinafter AITS) (Arranz et al., 2023; Lee et al., 2022). The first convergence is established through the connection between machines and automatic and deep learning algorithms, advances in computing capacity (cloud computing), and the analysis and management of big data (big data analytics). This first convergence can be called AI-based algorithms and software (hereinafter AIAS). The second convergence is established through the link between machines and automatic and deep learning algorithms and the equipment and devices that use them intensively, such as robots or intelligent devices. High-speed computing and communication infrastructures are required for this. This second convergence can be called AI-based hardware and infrastructure (hereinafter AIHI).

All this new convergent set of digital technologies and techniques gathered around the transformative potential of AI has been distancing itself from the technologies of the first digital wave (i.e., the non-interactive Internet and information and communication technologies), and has begun to develop a transition process within the digital paradigm and industry 4.0 (hereinafter I4.0) (Benitez et al., 2023; Eurofound, 2020). Recently, these new AITS have been called I4.0 enabling technologies, intelligent technologies or digital transition technologies (Martinelli et al., 2021; Torrent-Sellens, 2024; Venturini, 2022). In economic and business terms, the advent of AITS has led to the emergence of a new source of economic value, predictive value (Agrawal et al., 2019; Brynjolfsson et al., 2021), which has evolved beyond the traditional calculation, information, and communication values associated with the first digital wave (Torrent-Sellens, 2024).

In current times of global environmental emergency, fragile planetary boundaries, and an uncertain socioeconomic future characterised

* Corresponding author.
*E-mail addresses:* jtorrent@uoc.edu (J. Torrent-Sellens), cenachez@uoc.edu (M. Enache-Zegheru), pficapal@uoc.edu (P. Ficapal-Cusí).

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by increasing polarisation and inequalities, societies are increasingly aware of the need to promote a profound ecological and social transition in their methods of economic organisation and production (Green & Healy, 2022; Singer, 2018). To this end, digital transition technologies, particularly AITS, if implemented properly, can be highly relevant instruments (Kar et al., 2022; Nishant et al., 2020). Indeed, the ecological transition -with green growth, social and environmental innovation, and the circular economy as its main pillars- and the digital transition -with AITS as the main technologies-are central and interrelated priorities of the current mandate of the European Commission for a double transition towards a more just and balanced digital and socio-environmental future (European Commission, 2022; Muench et al., 2022).

Economic and business research has not been immune to the growing social and political demand, which has been organised under the heading of the twin transition (Chen et al., 2023). Research on digital, social, and ecological transitions has made notable contributions from both historical perspectives (Fouquet & Hippe, 2022) and in guiding public policy (Dwivedi et al., 2022). From a business perspective, evidence has begun to emerge about the antecedents and initial complementarities of these transitions (Ortega-Gras et al., 2021), as well as some preliminary results (Montresor & Vezzani, 2023; Rehman et al., 2023). Nevertheless, despite the shared objectives of the digital and socio-environmental transitions within the scientific community, the paths to achieving these goals have generated significant political controversies and strategic implementation challenges (Collini & Hausemer, 2023; Hellemans et al., 2022). Technophile or techno-optimist positions, which arise from technical solutionism, argue that the digital transition, particularly the responsible use of AITS, will be fundamental for optimising and increasing the efficiency of business operations (Dubey et al., 2019; Dwivedi et al., 2021). This new cycle of sustainability is expected to be based on economic growth linked to massive data and tasks and their new predictive values (Agrawal et al., 2022; Nuccio & Guerzoni, 2019). On the other hand, more critical lines of interpretation have emerged. Prioritising behavioural problems and criticising technological solutionism, this literature highlights the limits and contradictions that the digital transition imposes on social and natural systems, proposing scenarios of post-growth, degrowth, and deconstruction of capitalism (Hickel & Kallis, 2020; Slameršak et al., 2024).

In this article, we aim to advance this debate and explore whether innovation dimensions and the digital transition can be leveraged to build pathways toward social and environmental sustainability. To this end, we focus on a specific subset of the digital field—AI—and pose the following research questions: Can AI-based technologies and social and environmental innovation mediate and accelerate the relationship between economic innovation and economic, social, and environmental sustainability? How does a digital innovation strategy moderate and enhance the relationship between AI-based technological systems and sustainability across environmental, economic, and social dimensions? To answer these questions, we draw on a large, representative sample of 12,326 European micro, small, and medium enterprises (hereinafter MSMEs) from 2020. Our results suggest the existence of various possible sustainability pathways for European MSMEs. However, the heterogeneity of AI adoption and use, geographical diversity, and the inherent limitations of this research call for interpretative caution to avoid excessively technology-solutionist implications and misguided public policies.

## 2. Theoretical framework and hypotheses

Although the direct link between the digital transition and the ecological transition has recently been established as a key objective for a more just and sustainable socioeconomic future (Diodato et al., 2023; Sharma et al., 2020), economic and business research has been analysing the relationship between technology and innovation; environmental management strategies, investments, and practices; and business outcomes in terms of sustainability—aligned with the economic, social, and environmental triple bottom line (de Sousa Jabbour et al., 2018; Ghobakhloo, 2020; Torrent-Sellens et al., 2023)—for over two decades.

One widely supported finding is that economic innovation and technology can enhance firms' economic, social, and environmental sustainability outcomes (Adams et al., 2016; Shrivastava, 1995). When firms adopt a proactive approach to regulation or environmental quality systems, economic innovation and technology can foster complementary relationships that create win-win scenarios, where the pursuit of environmental sustainability also enhances firm competitiveness. This aligns with the Porter Hypothesis (Dangelico & Pontrandolfo, 2015; Porter & van der Linde, 1995). However, not all technologies or innovations have similar effects. The literature highlights that technologies or economic innovations that improve efficiency, such as green technologies (Dangelico et al., 2017; Mehmood et al., 2024), or those that drive structural changes in value chains—enhancing productivity or reducing costs—are more effective in promoting economic and social sustainability (Ghisetti & Rennings, 2014; Ozusaglam et al., 2018; Torrent-Sellens et al., 2023).

Similarly, research has found clear links between the presence of product, process, organisational, and marketing-related economic innovations and corporate social responsibility practices, leading to improvements in environmental and social sustainability indicators (Aguilera et al., 2024; Mithani, 2017; Saha et al., 2020). Technologies or innovations that reduce externalities, such as end-of-pipe environmental practices aimed at reducing emissions or pollution, primarily focus on generating synergies and complementarities with environmental sustainability (Opazo-Basáez et al., 2024; Ramanathan et al., 2017; Rexhäuser & Rammer, 2014). Given this evidence, the first three research hypotheses of this article can be postulated, both referring to the relationship between economic innovation and economic, environmental and social sustainability.

**Hypothesis 1a**. Economic innovation has a positive effect on MSME economic sustainability

**Hypothesis 1b**. Economic innovation has a positive effect on MSME environmental sustainability.

**Hypothesis 1c**. Economic innovation has a positive effect on MSME social sustainability.

Similarly to economic innovation, a second important finding identified in the literature is that not all assets and dynamic capabilities generate the same incremental outcomes in terms of social and environmental sustainability (Epstein et al., 2015; Singh et al., 2020). The theory of dynamic capabilities distinguishes between ordinary capabilities, which relate to the normal operations of firms, and dynamic capabilities, which are higher-level assets, resources, or innovations. These capabilities—through sensing (detecting unknown futures), seizing (exploiting valuable resources), and reconfiguring (continuous transformation)—enable firms to acquire new forms of competitive advantage (Teece, 2014).

Specifically, dynamic capabilities can be defined as: "the firm's ability to integrate, build and reconfigure internal and external competencies to address rapidly changing environments. Therefore, dynamic capabilities reflect an organisation's ability to achieve new and innovative forms of competitive advantage given path dependencies and market positions" [56, p. 516].

Dynamic capabilities encompass a broad spectrum of skills, processes, procedures, organisational structures, decision rules, and disciplines (Teece, 2007). However, their evolution must always be oriented towards the identification of opportunities, their exploitation, and subsequent reconfiguration to achieve new sources of competitive advantage. Among other sources of dynamic competitive advantage, research has identified learning and supporting experimentation, resource recombination, new product development, and transformation of production systems (Teece, 2016).

In this context, research on sustainable dynamic capabilities has indicated that adaptation to environmental legislation and regulations, the incorporation of environmental quality systems, and the mobilisation of certain dynamic capabilities are key elements in achieving a return on environmental action (Buzzao & Rizzi, 2021; Eikelenboom & de Jong, 2019). These key factors include a commitment to sustainability values and culture, the capacity for absorption and adaptability to external measures, organisational redesign and flexibility, the presence of sustainable assets and management systems, technological innovation, R&D systems, the reorientation of the business model towards social and environmental sustainability, the analysis and management of enriched data, the presence of internal and external sustainability networks, and the management of workers' knowledge, skills, and capabilities for sustainable human resource management (Bari et al., 2022; Bhadra et al., 2024; Mousavi et al., 2018).

Likewise, innovations aimed at social responsibility (social innovation) and the ecological or green transition (environmental innovation), when complemented by the use of various digital technologies, yield incremental improvements in both social (Faludi, 2023; Gupta et al., 2020) and environmental (Cannavacciuolo et al., 2023; Ghobakhloo et al., 2021; Raj & Jeyaraj, 2023) sustainability. Given this evidence, we put forward our second research hypothesis, which highlights the dynamic capabilities linked to social and environmental innovation processes. In this regard, we propose.

**Hypothesis 2a**. Environmental innovation plays a mediating role in promoting the relationship between economic innovation and MSME environmental sustainability

**Hypothesis 2b**. Social innovation plays a mediating role in promoting the relationship between economic innovation and MSME social sustainability.

In the same vein, research on digital transformation has also identified a range of dynamic capabilities for firms and their digital transformation processes (Ellström et al., 2022). These capabilities are linked to digital sensing, seizing, and reconfiguring and manifest through a combination of changes in culture and values, strategic opportunity detection, modification of organisational structure, innovation and adaptation of the business model, integration of internal and external networks for digital transformation, and the development of new capabilities and skills for employees and managers (Ghobakhloo et al., 2023; Ghosh et al., 2022; Kopka & Fornahl, 2024).

By integrating both bodies of literature, recent research on the digital and socio-ecological transition has also identified similar dynamic capabilities and pathways (Chen et al., 2023; Collini & Hausemer, 2023; Ortega-Gras et al., 2021). In this context, evidence is emerging on how firms mobilise other complementarities within the twin digital and socio-environmental transition (Ferreira et al., 2022; Guandalini, 2022; Opazo-Basáez et al., 2024).

However, despite the high expectations generated, research on AI and its links to sustainability pathways in firms remains limited (Chen et al., 2024; Kar et al., 2022). There is some evidence of the relationship between AI adoption and social sustainability, particularly in terms of job creation and corporate social responsibility (Chen et al., 2023; Yang, 2022). Similarly, AI usage has been associated with firm-level environmental sustainability, especially concerning pollution reduction, decarbonisation, and energy savings (Dubey et al., 2020; Mehmood et al., 2024; Rehman et al., 2023). Lastly, there is also some evidence of the complementarity between AI and economic innovation (Babina et al., 2024; Grashof & Kopka, 2023; Mariani et al., 2023). Given this evidence, and following the recommendations of the literature on AI and its effects (Haefner et al., 2021; Krakowski et al., 2023), we propose the third research hypothesis, which highlights the dynamic capabilities linked to the adoption and use of AI-based technological systems.

**Hypothesis 3a**. AI-based technological systems play a mediating role in promoting the relationship between economic innovation and MSME economic sustainability

**Hypothesis 3b**. AI-based technological systems play a mediating role in promoting the relationship between economic innovation and MSME environmental sustainability.

**Hypothesis 3c**. AI-based technological systems play a mediating role in promoting the relationship between economic innovation and MSME social sustainability.

The concept of the twin transition, which integrates the ecological transition—underpinned by green growth, social and environmental innovation, and the circular economy—along with the digital transition, driven primarily by AI-based technological systems (AITS), represents a key and interconnected priority in the European Commission's current agenda. It has also garnered increasing academic interest due to its impact on firms' sustainability pathways. While research has highlighted the potential complementarities between these two transitions (Montresor & Vezzani, 2023; Ortega-Gras et al., 2021; Rehman et al., 2023), a significant debate remains regarding the extent to which they reinforce or substitute each other (Montresor & Vezzani, 2023; Rehman et al., 2023) and the challenges they present (Collini & Hausemer, 2023; Hellemans et al., 2022).

Research supporting the complementarity perspective has provided evidence that digital technologies enable green innovation (Ning et al., 2023; Wei & Sun, 2021), optimise access to resources and value creation (Castillo Esparza et al., 2024; Martínez-Caro et al., 2020), and enhance firms' innovation and sustainability performance (Rehman et al., 2023). Industry 4.0 technologies, such as AI, big data analytics, and IoT, have been shown to support firms in achieving green competitive advantage by integrating environmental efficiency into business operations (Rehman et al., 2023). Moreover, a strong digital innovation strategy can facilitate circular economy practices, optimise supply chains, and enhance transparency, thereby strengthening the link between AI-based systems and sustainability performance (Torres de Oliveira et al., 2023).

Conversely, the substitution effect highlights the trade-offs between digital transformation and sustainability objectives, where the impact of digital investments varies depending on the composition of ICT profiles and their strategic alignment with sustainability goals (Tekic & Tekic, 2024). While AI-based technological systems have demonstrated efficiency improvements, as industrial robots enhance energy efficiency and reduce pollutant emissions (Zhou et al., 2024), their overall sustainability impact depends on technological implementation and regional factors.

Researchers have introduced the concept of the "IT production paradox", suggesting that the adoption of digital transformation can disrupt established processes and organisational frameworks, potentially leading to strategic misalignment (Srivastava et al., 2022) and adversely impacting business performance (Cappa et al., 2021). Moreover, firms integrated into multinational groups or corporations often face organisational inertia and institutional misalignment, particularly between headquarters and international subsidiaries, which complicates efforts to integrate digital transformation with sustainability initiatives (Torres de Oliveira et al., 2023).

Given these dynamics, digital innovation strategy influences the relationship between AI-based technological systems and sustainability dimensions, with effects that may be context-dependent rather than uniformly positive (Lu et al., 2023; Rehman et al., 2023). While AI-based technological systems enhance efficiency and productivity, their economic impact is influenced by firms' ability to effectively integrate them into their strategic models, as high investment costs and operational complexities may limit their scalability for MSMEs (Rehman et al., 2023). Moreover, digital innovation strategies often emphasize technological competitiveness and automation, leading to both positive and negative sustainability outcomes (Tekic & Tekic, 2024). However, a misaligned digital innovation strategy may exacerbate workforce displacement and job polarisation, posing challenges for social sustainability (George, 2024). The impact of AI adoption on economic, environmental, and social sustainability is contingent upon the composition and quality of digital innovation strategies, as different ICT profiles yield varying sustainability outcomes. While some digital strategies enhance sustainability performance, others present trade-offs that may challenge the simultaneous achievement of economic, environmental, and social objectives (Tekic & Tekic, 2024). Thus, we propose that.

**Hypothesis 4a.** Digital innovation strategy moderates the relationship between AI-based technological systems and MSME economic sustainability.

**Hypothesis 4b.** Digital innovation strategy moderates the relationship between AI-based technological systems and MSME environmental sustainability.

**Hypothesis 4c.** Digital innovation strategy moderates the relationship between AI-based technological systems and MSME social sustainability.

## 3. Methods

### *3.1. Sample*

This research uses data from the Flash Eurobarometer 486: SMEs, start-ups, scale-ups, and entrepreneurship (European Commission, 2020). The fieldwork was conducted through telephone interviews from February to May 2020. The sample consists of 12,326 European MSMEs and collects information on digital transformation and sustainable development in 29 European Union countries. This database has already been used in several studies on the adoption and results of digital transformation in European firms (Arranz et al., 2023; Arroyabe et al., 2024). The data were segmented by MSMEs size as follows: 7143 microfirms, and 5183 SMEs, with the aim of obtaining deeper insights on sustainability pathways and organisational size differences.

### *3.2. Variables*

The construct of economic innovation (ECINN) combines innovations in products or services, processes, organisational/business models, and marketing/commercialisation. Each component is binary (1, if it applies an innovative practice). The combined value of these components forms the variable, which ranges from 0 to 4.

To develop the AI-based technological system indicator (AITS), two constructs were identified. The first construct, referring to AI-based algorithms and software (AIAS), encompasses the use of three technologies: machine learning algorithms, cloud computing and big data analytics. The values of this construct range between 0 (no use) and 3 (when the three specified technologies are used). The second construct, AI-based hardware and infrastructure (AIHI), includes the use of three technologies: robotics, smart devices (such as sensors or drones), and high-speed infrastructure. As in the previous case, its values range between 0 and 3. The composite AITS indicator integrates the AIAS and AIHI constructs, resulting in values ranging from 0 to 6.

Social innovation (SOCINN) integrates innovations that benefit society, such as the development of new products or processes aimed at social improvement. Environmental innovation (ENVINN) reflects innovations that benefit the environment, such as efficiency improvements in resource or energy management. Due to the binary nature of the input variables, SOCINN and ENVINN values range from 0 to 1.

Digital innovation strategy (DIS) integrates three binary components: having a strategy or action plan for going digital, pursuing growth via innovation, and aiming for growth through digitalization advancement. Each component is assigned a value of 1 if the criterion is met and 0 otherwise. The combined score, which ranges from 0 to 3, represents the extent to which the firm actively engages in and strategizes digital innovation.

Economic Sustainability (ECSUS) captures a MSMEs' commitment to sustainable economic growth by integrating its sales growth forecasts, employee growth forecasts, and the presence and maturity of a sustainability plan. The first two indicators use a scale from 1 to 5, where 1 denotes no plans or uncertainty and higher values represent greater anticipated growth. The sustainability plan is evaluated from 0 (no plan) to 3 (fully implemented), reflecting the degree to which the firm aligns economic success with social and environmental considerations. When combined, these recoded values form ECSUS, with higher scores indicating a stronger orientation toward sustainable economic development.

Environmental sustainability (ENVSUS) is measured through the implementation of circular economy practices (CIRCSUS) and environmental sustainability practices related to products (PRODSUS). CIRCSUS includes recycling, material reuse, and reduction of natural resource consumption or impact, while PRODSUS includes innovations related to energy savings, the transition to sustainable energy sources, and the development of more sustainable products or services. Each construct has two binary variables, resulting in a range of values for ENVSUS from 0 to 4.

Social sustainability (SOCSUS) is evaluated through two constructs reflecting the firm's internal and external social responsibility efforts. Internal social sustainability (INTSOCSUS) includes actions to improve working conditions, job quality, and employee engagement in corporate governance, while external social sustainability (EXTSOCSUS) evaluates actions to promote diversity, workplace equality, and the firm's social impact. Both the internal and external social sustainability constructs have two binary variables, leading to an aggregate range of values for the SOCSUS indicator from 0 to 4. The constructs and variables used in the analysis are presented in Annex 1.

### *3.3. Analysis*

The models were examined using partial least squares structural equations modelling (PLS-SEM). The SmartPLS4 software was used both to assess the measurement model and to test the structural model (Ringle et al., 2015). Since this research aims to predict key target constructs without assuming any prior distribution of the data, as a non-parametric method, PLS-SEM is preferable to other covariance-based prediction methods (Hair et al., 2017).

## 4. Results

### *4.1. Measurement models*

Before evaluating the structural model, the measurement models were assessed to test their internal consistency, convergent validity, and discriminant validity (Roldán & Sánchez-Franco, 2012) (see Table 1). To

**Table 1**
Results of the measurement models.

| Constructs | Microfirms | | | | SMEs | | | MSMEs | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Indicators | Loadings | ρc | AVE | Loadings | ρc | AVE | Loadings | ρc | AVE |
| AITS | AIAS | 0.833 | 0.824 | 0.701 | 0.838 | 0.832 | 0.713 | 0.840 | 0.835 | 0.716 |
| | AIHI | 0.842 | | | 0.850 | | | 0.853 | | |
| ECSUS | SUSPLA | 0,584 | 0.784 | 0.553 | 0.653 | 0.756 | 0.509 | 0.628 | 0.776 | 0.538 |
| | EGF | 0.798 | | | 0.729 | | | 0.769 | | |
| | SGF | 0.825 | | | 0.753 | | | 0,792 | | |
| ENVSUS | CIRCSUS | 0,851 | 0.869 | 0.768 | 0.843 | 0.864 | 0.760 | 0.851 | 0.868 | 0.767 |
| | PRODSUS | 0.901 | | | 0.899 | | | 0.900 | | |
| SOCSUS | EXTSOCSUS | 0,890 | 0.879 | 0.785 | 0.890 | 0.872 | 0.772 | 0.892 | 0.878 | 0.783 |
| | INTSOCSUS | 0.882 | | | 0.868 | | | 0.878 | | |
| DIS | GVI | 0.684 | 0.779 | 0.541 | 0.670 | 0.780 | 0.543 | 0.673 | 0.780 | 0.543 |
| | GVD | 0.726 | | | 0.718 | | | 0.719 | | |
| | ACT | 0.793 | | | 0.815 | | | 0.811 | | |

*Notes*: Loadings. pc: composite reliability. AVE: average variance extracted.

evaluate internal consistency, composite reliability (ρc) was used, yielding values greater than 0.7. Additionally, convergent validity was assessed by examining the relevance of the outer loadings of indicators, with a critical acceptance value of 0.7, except for the ACT and GVI items, whose loadings are slightly below this threshold, and the average variance extracted (AVE) of all constructs, which exceeded the threshold of 0.5 (Henseler et al., 2015). Moreover, while certain ACT and GVI indicators exhibited factor loadings marginally below the 0.7 threshold, their retention was deemed justifiable due to their theoretical importance and the broader model context. In addition, the high AVE values across all constructs indicate that a substantial proportion of variance in the indicators is attributable to their respective latent variables, further reinforcing the adequacy of the measurement model in terms of convergent validity.

On the other hand, Annex 2 presents the analysis of the discriminant validity of the measurement models. The square root of each AVE value is higher than the correlations of the latent variables (Fornell & Larcker, 1981), and the Heterotrait-Monotrait ratio (HTMT) is satisfactory, with values below 0.85, indicating that the constructs are conceptually distinct (Hair et al., 2017; Henseler et al., 2015). Additionally, an initial bootstrapping analysis with 5000 samples confirmed that the HTMT values differ significantly from 1, providing further evidence of discriminant validity for all the constructs used.

### 4.2. Structural models

#### 4.2.1. Direct and mediating effects

Prior to assessing the structural models, we evaluated the variance inflation factor (VIF) values, which are all below 5 (Ringle et al., 2015), indicating the absence of multicollinearity. The path coefficients of the model and their statistical significance were estimated using the bootstrapping technique, based on 5000 subsamples. One-tailed tests of direct effects were performed using a Student's t-distribution with a 95% confidence interval. Annex 3 presents all the tables that reflect the direct effects, their significance, explained variance, and effect size for each of the firms analysed. In all of them, it is observed that the direct effects are significant at the 0.001 level ($t \geq 3.092$) and that the confidence intervals do not include the value 0, with the exception of the moderating effect of Digital innovation strategy in the relationship between AI-based technological systems and economic sustainability for small and middle size firms and the total sample of MSMEs. Similarly, Annex 4 presents the results of the hypothesised indirect effects for each of the firm dimension. As in the previous case, the values of the indirect coefficients, their significance, and interpretation are presented. Thus, economic innovation provides a basis for assessing the mediating role of social and environmental innovations and AI-based technological systems as well as for establishing pathways towards social, economic, and environmental sustainability. Furthermore, the moderating effect of AI-based technological systems on the sustainability dimensions is also evaluated.

In general, the R2 values exceed 0.1, indicating an adequate explanatory power (Srivastava et al., 2022), except for the construct of AI-based technological systems, Environmental innovation, in the case of microfirms and Economic sustainability in the case of small and medium size companies. Environmental sustainability exhibits the highest explained variance in the case of small and middle size firms (0.258), followed by social sustainability (0.247) in the same group of companies. Cohen's f2 was used to evaluate the effect size, many pathways meet or exceed the Cohen's threshold of 0.02, indicating significant effects. This suggests that most of the study variables are significant predictors of their respective exogenous variables (Roldán & Sánchez-Franco, 2012). However, several pathways, especially those involving DIS as a moderator, fall below this threshold, suggesting weaker effects in those cases. Overall, the majority of direct effects on sustainability measures are significant, with particularly strong influences noted in ECINN to AITS and environmental or social innovations.

In Fig. 1, the sustainability pathways for microfirms are shown. All direct effects are significant, as reflected in Table A.3.1. Economic innovation is a driver of AI-based technological system adoption ($\beta = 0.288$, $p < 0.001$). This relationship suggests that microfirms engaging in innovations related to products, processes, organizational structures, or marketing are more likely to adopt AI-based technologies. These technologies, which encompass AI-based algorithms, hardware, and infrastructure, serve as an important enabler of sustainability practices, reinforcing the connection between innovation and digital transformation in microfirms.

The indirect effect of economic innovation on environmental sustainability through environmental innovation, and on social sustainability through social innovation, is significant, as the confidence intervals do not include 0 (see Table A.4.1). Economic innovation drives the adoption and development of AI-based technological systems, which, in turn, positively affect sustainability dimensions. In other words, the ability of AI to improve efficiency, optimise processes, develop sustainable products, and manage resources more effectively is essential for translating economic innovation into circular economy practices and the environmental sustainability of products. Additionally, AI adoption fosters microfirms' internal and external social

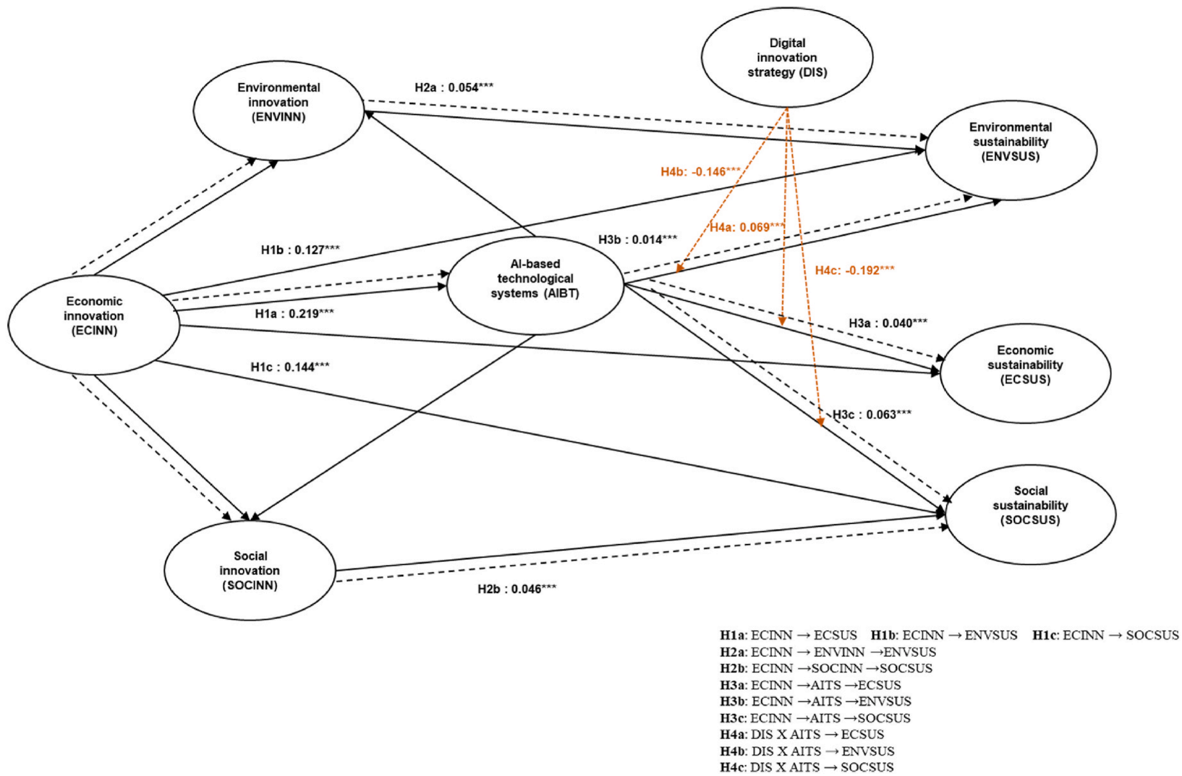


**Fig. 1.** Sustainability pathways in European microfirms.
Notes ***p < 0.001. Direct effects: Mediation effects: Moderating effects.

responsibility efforts, as well as their commitment to sustainable economic growth, which is reflected in sales growth forecasts, employee growth forecasts, and the presence and maturity of a sustainability plan.

The results reveal a nuanced role of Digital Innovation Strategy (DIS) in moderating the relationship between AI-based technological system adoption and sustainability dimensions in microfirms. While DIS

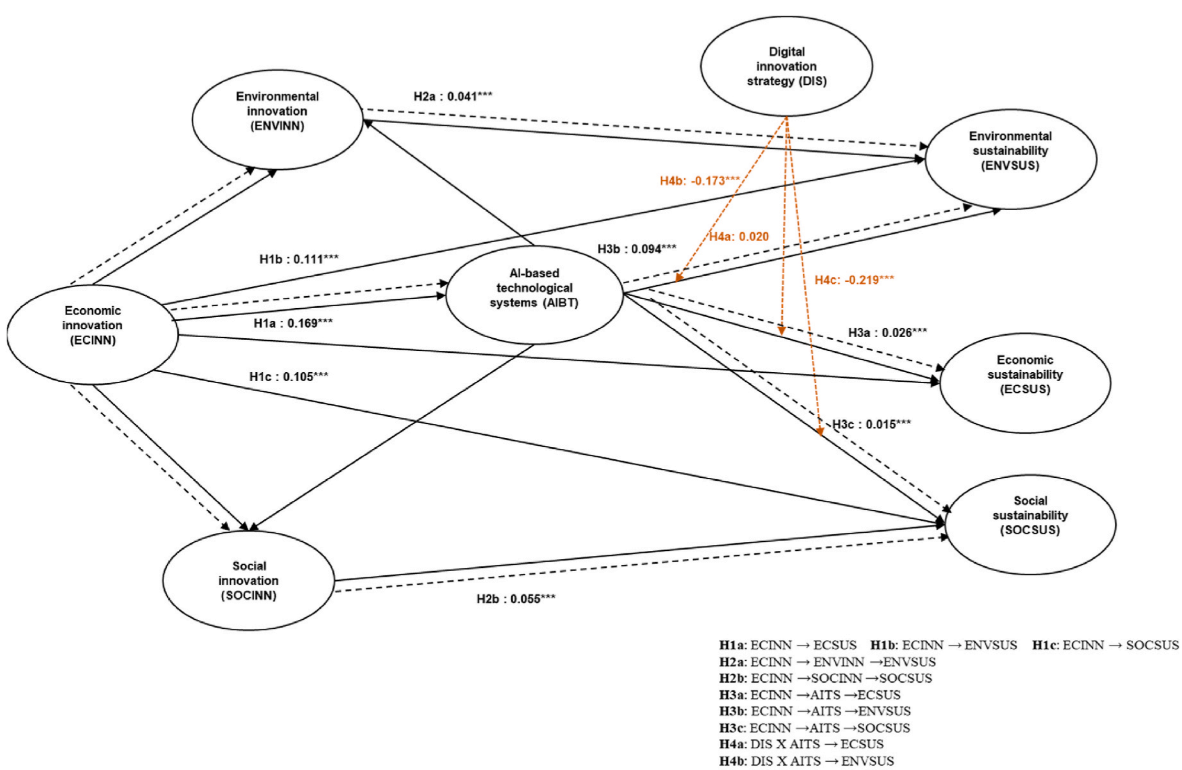


**Fig. 2.** Sustainability pathways in European SMEs.
Notes ***p < 0.001. Direct effects: Mediation effects: Moderating effects.

enhances economic sustainability outcomes, it appears to constrain the environmental and social benefits of AI adoption (see Fig. 1 and Table A.3.1). In the case of environmental sustainability, the negative moderation effect of DIS suggests that an overly focused on automation and control digital innovation strategy may reduce the positive influence of AI-based technological adoption. This finding indicates that highly structured strategic frameworks could limit the flexibility required for AI to effectively drive sustainability-oriented environmental innovations. Microfirms that impose rigid digital strategies may struggle to leverage AI's full potential for optimising resource efficiency, saving energy, switching to sustainable energy sources, and advancing circular economy practices.

Conversely, for economic sustainability, DIS exerts a positive moderation effect, reinforcing the economic benefits derived from AI adoption. However, the findings for social sustainability reveal a negative moderation effect, suggesting that DIS may impose constraints on AI's ability to foster socially responsible practices. While AI adoption generally supports social sustainability through improved organizational efficiency and stakeholder engagement, a digital strategy focused on automation and control may limit adaptability, reducing AI's effectiveness in enhancing internal and external social responsibility efforts.

Finally, the model highlights that ENVSUS ($R^2 = 0.193$) and ECSUS ($R^2 = 0.123$) have moderate explanatory power, with SOCSUS showing the strongest explained variance (22.1%).

Fig. 2 reflects sustainability pathways for European SMEs. The direct effect of economic innovation on AI-based technological systems is significant ($\beta = 0.309$, $p < 0.001$).), indicating that increases in product, process, organisational, or commercial innovation are associated with greater adoption of AI-based technologies, thus suggesting that firms with innovative practices tend to adopt more AI technologies. Additionally, as reflected in Table A.3.2., there is a significant direct relationship between economic innovation and social and ($\beta = 0.116$, $p < 0.001$) environmental innovation ($\beta = 0.099$, $p < 0.001$), which in turn positively affects social and environmental sustainability ($\beta = 0.357$ and 0.515, respectively, $p < 0.001$). Furthermore, AI-based technological systems significantly impact both environmental ($\beta = 0.306$, $p < 0.001$) economic sustainability (ECSUS) ($\beta = 0.177$, $p < 0.001$), and social sustainability ($\beta = 0.338$, $p < 0.001$). This indicates that firms generating more social and environmental innovations and those adopting AI tend to implement more circular economy practices and product-related environmental sustainability practices, as well as demonstrate internal and external social responsibility efforts. The model explains 25.8% of the variance in environmental sustainability and 24.7% of the variance in social sustainability.

The moderation results indicate that Digital Innovation Strategy (DIS) plays a complex role in shaping the impact of AI-based technological system (AITS) adoption on sustainability dimensions in SMEs. While AI adoption positively influences all sustainability dimensions, the interaction with DIS exhibits mixed effects, with respect to economic, environmental, and social sustainability.

For environmental sustainability, the negative moderation effect ($\beta = -0.173$, $p < 0.001$) suggests that a strong DIS reduces the positive influence of AI adoption on environmental outcomes. This finding implies that overly structured digital strategies may constrain AI's potential to drive ecological improvements, possibly by limiting the flexibility needed for AI-driven resource optimization and circular economy practices.

In the case of economic sustainability, the moderation effect of DIS is not statistically significant ($\beta = -0.020$, $t = 0.671$, $p > 0.05$), indicating that DIS does not substantially alter the relationship between AI adoption and economic outcomes. This suggests that, unlike in microfirms, SMEs may already benefit from AI-driven economic gains regardless of the level of digital strategy implementation.

For social sustainability, DIS exerts a significant negative moderation effect ($\beta = -0.219$, $t = 8.370$, $p < 0.001$), indicating that a strong digital strategy weakens AI's positive impact on social sustainability.

For the total sample, economic innovation also positively impacts social innovation ($\beta = 0.127$, $p < 0.001$) and environmental innovation ($\beta = 0.098$ $p < 0.001$). Social innovation drives social sustainability ($\beta = 0.350$ $p < 0.001$), demonstrating that societal-focused innovations are essential for improving internal and external social responsibility. Similarly, environmental innovation positively contributes to environmental sustainability ($\beta = 0.544$, $p < 0.001$), as reflected in Table A.3.3.

The moderation results for the total sample (MSMEs) reinforce the findings observed separately for microfirms and SMEs, highlighting a complex role of DIS in shaping the impact of AI-based technological system (AITS) adoption on sustainability dimensions.

For environmental sustainability, DIS exhibits a significant negative moderation effect ($\beta = -0.152$, $p < 0.001$). This result is consistent with the negative moderation effects observed in both microfirms and SMEs, suggesting that rigid strategic frameworks may hinder AI-driven ecological improvements.

Regarding economic sustainability, the moderation effect of DIS is not significant ($\beta = -0.000$, $t = 0.020$, $p > 0.05$), confirming the pattern observed in SMEs, where digital strategy does not substantially alter the relationship between AI adoption and financial performance. This suggests that AI's economic benefits materialize independently of the level of strategic digitalization.

For social sustainability, DIS again negatively moderates the effect of AI adoption ($\beta = -0.207$, $t = 11.615$, $p < 0.001$), reinforcing the results from microfirms and SMEs. This suggests that while AI positively contributes to social sustainability, a highly structured digital strategy may introduce constraints that reduce its effectiveness in fostering socially responsible business practices (see Fig. 3).

The model highlights that economic innovation and AITS are central to achieving sustainability outcomes in European microfirms and SMEs. Social innovation is a key driver of social sustainability, while environmental innovation and digital strategies contribute to environmental goals. The relationships suggest that combining innovation and technology can significantly enhance sustainability practices across diverse dimensions in this group of firms.

### 4.2.2. Hypotheses testing

The hypotheses testing results reveal distinct patterns across microfirms, SMEs, and the total sample, highlighting the varying impacts of economic innovation and AI-based technological systems on sustainability outcomes.

The research results confirm that economic innovation positively influences economic, environmental, and social sustainability in European microfirms, SMEs, and MSMEs. However, the magnitude of these effects varies, suggesting that firm size plays an important role in determining the extent to which economic innovation contributes to sustainability.

Regarding economic sustainability, the results indicate that economic innovation exerts a statistically significant positive effect across all firm sizes, thus supporting Hypothesis 1a. These results are consistent with previous research (Ghisetti & Rennings, 2014; Ozusaglam et al., 2018; Torrent-Sellens et al., 2023). However, the strength of the relationship varies, with the highest effect observed in microfirms ($\beta = 0.219$, $p < 0.001$), followed by MSMEs ($\beta = 0.203$, $p < 0.001$), and the lowest in SMEs ($\beta = 0.169$, $p < 0.001$). These findings suggest that smaller firms may be more agile in integrating economic innovations to enhance their economic sustainability.

Consistent with previous research (Opazo-Basáez et al., 2024;

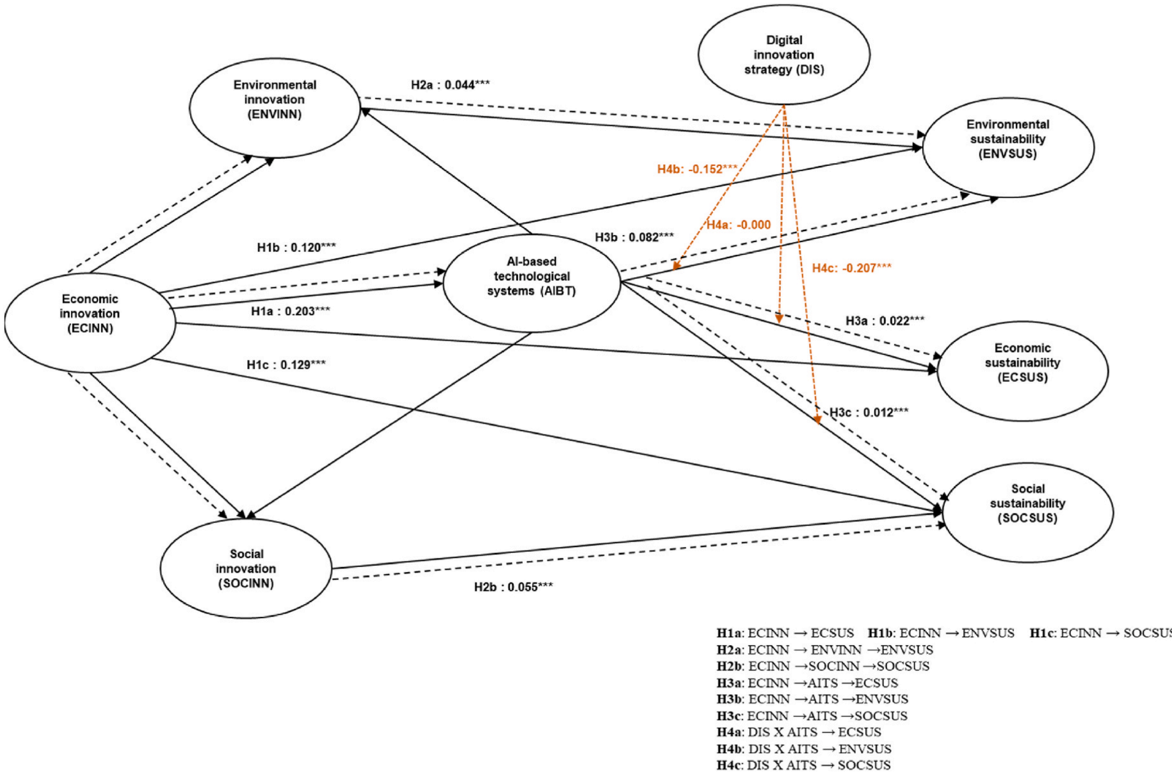


**Fig. 3.** Sustainability pathways in European MSMEs.
Notes ***p < 0.001. Direct effects: Mediation effects: Moderating effects.

Ramanathan et al., 2017; Rexhäuser & Rammer, 2014), the relationship between economic innovation and environmental sustainability follows a similar trend but with relatively weaker effects across all firm sizes, thus supporting Hypothesis 1b. Economic innovation significantly enhances environmental sustainability in microfirms ($\beta = 0.127$, $p < 0.001$), MSMEs ($\beta = 0.120$, $p < 0.001$), and SMEs ($\beta = 0.111$, $p < 0.001$).

The impact of economic innovation on social sustainability is also statistically significant across all firm sizes, thereby confirming Hypothesis 1c and aligning with previous research findings (Aguilera et al., 2024; Mithani, 2017; Saha et al., 2020). However, the effect is strongest in microfirms ($\beta = 0.144$, $p < 0.001$), followed by MSMEs ($\beta = 0.129$, $p < 0.001$), and weakest in SMEs ($\beta = 0.105$, $p < 0.001$). These findings indicate that smaller firms may be more effective in translating economic innovation into social benefits, such as improved working conditions, employee engagement, and stakeholder relationships.

Hypotheses 2 and 3 tested the mediating effect of green innovation, social innovation, and AI-based technological systems in linking economic innovation to sustainability dimensions. The results confirm that green innovation partially mediates the relationship between economic innovation and environmental sustainability (H2a) across microfirms and SMEs, with the effect being strongest in microfirms ($\beta = 0.054$, $t = 12.905$, $p < 0.001$), followed by MSMEs ($\beta = 0.044$, $t = 14.045$, $p < 0.001$), and slightly lower in SMEs ($\beta = 0.041$, $t = 9.575$, $p < 0.001$). These results support Hypothesis 2a, indicating that microfirms may be more agile in implementing green innovation strategies that enhance environmental sustainability.

Similarly, the results show that social innovation significantly mediates the relationship between economic innovation and social sustainability (H2b) in microfirms and SMEs. The effect is strongest for SMEs ($\beta = 0.055$, $t = 7.809$, $p < 0.001$), followed by MSMEs ($\beta = 0.055$, $t = 12.723$, $p < 0.001$), and slightly lower for microfirms ($\beta = 0.046$, $t = 9.909$, $p < 0.001$). These findings confirm Hypothesis 2b.

The results confirm that AI-based technological systems partially mediate the relationship between economic innovation and economic sustainability (H3a) across all firm sizes, The mediation effect is strongest in microfirms ($\beta = 0.040$, $t = 7.869$, $p < 0.001$), followed by SMEs ($\beta = 0.026$, $t = 11.202$, $p < 0.001$), and lower in MSMEs ($\beta = 0.022$, $t = 14.774$, $p < 0.001$), thus supporting Hypothesis 3a. The stronger mediation effect in microfirms suggests that small businesses are more agile in integrating AI-driven solutions to enhance economic sustainability, likely due to fewer bureaucratic barriers and a greater need for efficiency improvements. The weaker mediation effect in SMEs suggests that AI adoption may be more complex at larger scales, requiring more extensive infrastructure and workforce training.

The results also indicate that AI-based technological systems partially mediate the relationship between economic innovation and environmental sustainability (H3b), with the strongest effect in SMEs ($\beta = 0.094$, $t = 13.631$, $p < 0.001$), followed by MSMEs ($\beta = 0.082$, $t = 17.860$, $p < 0.001$), and significantly lower in microfirms ($\beta = 0.014$, $t = 8.767$, $p < 0.001$), confirming Hypothesis 3b.

The mediating role of AI-based technological systems in social sustainability (H3c) is also statistically significant but varies in intensity across firm sizes. The strongest mediation effect is observed in microfirms ($\beta = 0.063$, $t = 11.475$, $p < 0.001$), while the effect is much lower in SMEs ($\beta = 0.015$, $t = 7.304$, $p < 0.001$) and MSMEs ($\beta = 0.012$, $t = 9.743$, $p < 0.001$), thus supporting Hypothesis 3c. These findings indicate that microfirms benefit the most from AI adoption in promoting social sustainability. The significantly weaker effect in SMEs and MSMEs suggests that scaling AI-based social sustainability initiatives may be more complex in larger organizations, requiring more formalized implementation strategies.

Taken together, these insights suggest that firm size plays a critical role in shaping the effectiveness of different mediation pathways. While microfirms excel in leveraging AI for economic and social sustainability, SMEs are more effective in utilizing AI for environmental sustainability. The MSME-level results closely mirror SME trends, reinforcing the notion that larger firms within the MSME category tend to shape overall sustainability mediation patterns.

#### 4.2.3. Moderating effects

The moderating effects of the digital innovation strategy (DIS) on the relationship between AI-based technological systems (AITS) and sustainability dimensions—economic, environmental, and social—exhibit distinct patterns when segmented by organizational size, reflecting the unique challenges and priorities of microfirms and SMEs. For microfirms, DIS positively moderates the relationship between AITS and economic sustainability, with a coefficient of 0.069 ($p < 0.001$), suggesting that a strong digital innovation strategy enhances the ability of AI technologies to support sustainable economic growth. This finding indicates that microfirms with well-defined digital strategies can better utilize AI technologies to align their economic growth with sustainability goals. However, DIS has a negative moderating effect on the relationship between AITS and environmental sustainability, with a coefficient of −0.146 ($p < 0.001$). This implies that while microfirms adopt digital strategies, these strategies may not be effectively integrated with AI technologies to achieve environmental goals, potentially due to resource constraints or limited expertise. Similarly, DIS negatively moderates the relationship between AITS and social sustainability, with a significant coefficient of −0.192 ($p < 0.001$), suggesting that the implementation of digital strategies may create tension or trade-offs with efforts to enhance social responsibility in microfirms, which often operate with constrained resources.

In SMEs, the moderating effects of DIS reveal consistent negative relationships across all dimensions of sustainability, except the economic dimension. The relationship between AITS and economic sustainability is not influenced by DIS, with a non-significant coefficient of −0.020 ($p = 0.251$). This indicates that in SMEs, digital innovation strategies no moderating effect on how AI technologies contribute to economic sustainability, possibly due to competing priorities or the limited integration of digital strategies with economic goals. The negative moderating effect of DIS on the relationship between AITS and environmental sustainability is more pronounced, with a coefficient of −0.173 ($p < 0.001$), suggesting that even in larger organizations, digital strategies may not always align well with environmental goals. For social sustainability, the negative moderating effect of DIS is strongest, with a coefficient of −0.219 ($p < 0.001$), reflecting the challenges SMEs face in using digital strategies to enhance social impacts. This could result from competing priorities, where the focus on digital transformation may divert resources and attention from social responsibility initiatives.

For the total sample of MSMEs, the results largely mirror the trends observed in SMEs. The moderating effect of DIS on the relationship between AITS and economic sustainability is negligible and non-significant, with a coefficient of −0.000 ($p = 0.492$), indicating that DIS does not influence this relationship at the aggregate level. However, the moderating effect of DIS on the relationship between AITS and environmental sustainability remains negative and significant, with a coefficient of −0.152 ($p < 0.001$), reaffirming the challenges firms face in leveraging digital strategies to achieve environmental goals. The moderating effect of DIS on the relationship between AITS and social sustainability is the strongest, with a coefficient of −0.207 ($p < 0.001$), highlighting the persistent difficulties firms experience in integrating digital strategies with efforts to enhance social responsibility.

The differences in these moderating effects by organizational size can be attributed to varying capacities and strategic priorities. Microfirms, with their limited financial and human resources, often struggle to effectively integrate DIS with AI technologies for achieving sustainability goals, leading to positive effects on economic sustainability but negative effects on environmental and social sustainability. SMEs, despite having more resources than microfirms, may still face misalignments between digital strategies and sustainability objectives, particularly in the environmental and social dimensions. The complexity of implementing a digital innovation strategy alongside AI technologies further adds to these challenges, as firms of all sizes must navigate resource constraints, expertise gaps, and strategic trade-offs. These findings emphasize the importance of aligning digital strategies with broader sustainability goals to maximize the potential of AI technologies in both microfirms and SMEs.

## 5. Conclusions

### 5.1. Theoretical implications

This research examined the impact of the interaction between economic innovation, AI-based technological systems and social and environmental innovation upon firm environmental, economic and social sustainability. To this end, we tested four hypotheses based on a PLS-SEM econometric method and a sample of 12,326 small and middle-size European firms. The main analysis objectives have been to test: 1) whether economic innovation explains environmental and social innovation; 2) whether AI-based technological systems and social and environmental innovation mediate the relationship between economic innovation and environmental, economic and social sustainability, 3) as well as tackling the moderating role of digital innovation strategy in the relationship between AI-based technological systems and environmental, economic and social sustainability.

Despite the high expectations that have been generated, there is currently very little research analysing the social, economic and environmental sustainability pathways in firms as a result of the interaction between AI use and different types of innovation. Addressing this research gap is crucial because ecological and socio-environmental economics have long warned about the limitations and inadequacies of our responses to the climate emergency and social inequality.

Advancing in practices of investment in environmental assets, circular economy, and green growth, in addition to implementing social responsibility actions with stakeholders, seems to be an important pathway towards social and environmental sustainability, thus confirming hypotheses. For this, firms have a powerful technological and innovative.

This study enhances our theoretical understanding of sustainability pathways by integrating economic innovation, AI-based technological systems, and digital innovation strategies within a comprehensive framework. By examining these relationships in the context of European microfirms and SMEs, the study confirms that economic innovation serves as a key driver in the adoption of AI technologies and achieving sustainability outcomes, in line with the resource-based view (Barney, 1991, 1996, 2001) and innovation diffusion theories (Rogers, 2003). The segmentation by organisational size highlights the distinct roles that firm size plays in moderating the effectiveness of innovation strategies, enhancing theoretical understanding of how organisational capabilities influence sustainability outcomes. These findings build on the triple bottom line framework (Elkington, 1997), demonstrating the interconnectedness of economic, environmental, and social innovations towards achieving sustainable development.

The study also extends the discourse on digital transformation by revealing that while digital innovation strategies can support sustainability in some dimensions, they may also create strategic misalignments—particularly for smaller firms with limited resources. This nuanced finding challenges the assumption that digitalization and sustainability reinforce each other unconditionally. Instead, it highlights that when digital strategies place excessive emphasis on automation and control, they may marginalise ecological and social concerns, leading to potential trade-offs. This research contributes to the discourse on strategic alignment, emphasising the need for a more flexible and contextsensitive approach to integrating digital transformation and sustainability (Porter & Kramer, 2011). Additionally, the findings contribute to theoretical models on technology adoption, emphasising the differing impacts of AI-based software and hardware components on sustainability, which have been underexplored in prior literature (Brynjolfsson & McAfee, 2014).

### 5.2. Practical implications

Obtaining these sustainability pathways is important because they provide insights into firms' progression towards digital and socio-environmental transitions, and identify heterogeneous predictor factors in terms of innovation and AI usage. Our results suggest that differentiated business strategies and public innovation and digital transition policies are needed depending on the type of sustainability and firm size (Díaz-Chao et al., 2021; Paiho et al., 2023). A key implication in this context is the need for firms to activate the dynamic capabilities required to leverage digital transition for the benefit of sustainability (Díaz-Chao et al., 2021). External assistance is particularly valuable in this regard, especially for smaller firms. In the specific case of AI, given its still limited use, it seems evident that support policies and strategies for training people and for the self-selection of firms should be accelerated (Chhillar & Aguilera, 2022).

This research offers practical insights to foster sustainability in microfirms and SMEs. For microfirms, economic innovation emerges as driver of AI adoption and sustainability, highlighting the importance of fostering innovation in products, processes, and business models. Microfirms should prioritize targeted investments in innovation to unlock the potential of AI-based technologies (Babina et al., 2024). However, the findings also reveal that digital innovation strategies may negatively moderate the relationship between AI adoption and environmental or social sustainability. This suggests that microfirms need to carefully align digital strategies with resource capabilities to avoid potential trade-offs. Policymakers can support this alignment by providing tailored interventions, such as financial subsidies, capacity-building programs, and digital training initiatives designed specifically for microfirms.

For SMEs, the results indicate that digital innovation strategies can enhance sustainability dimensions when effectively integrated with technological adoption. SMEs should focus on aligning digital transformation initiatives with broader sustainability goals, such as circular economy practices and social responsibility efforts, to maximize the benefits of AI technologies. Moreover, the findings emphasize the importance of strategic investments in both AI-based hardware and software, as these technologies significantly contribute to economic and environmental sustainability. Policymakers should support these efforts by fostering collaborative platforms that enable knowledge sharing, thereby reducing the barriers SMEs face in implementing advanced digital technologies. These measures are particularly critical as SMEs play a key role in driving sustainable development across Europe.

### 5.3. Limitations

Despite the positive findings, the limitations of this research require a cautious interpretation of our conclusions to avoid technological solutionism (Naudé, 2021).

First, the reliance on self-reported data from the Flash Eurobarometer 486 may introduce response bias, as firms may overstate their engagement in innovation and sustainability practices. This limitation aligns with concerns raised in prior survey-based research (Podsakoff et al., 2024). Future studies should consider supplementing survey data with objective performance metrics, such as firm-level financial or environmental performance indicators, to validate the results. Second, the cross-sectional nature of the study limits the ability to infer causality between variables. Longitudinal studies could provide a more comprehensive understanding of how relationships between economic innovation, digital strategies, and sustainability evolve over time (Martínez-Caro et al., 2020).

Additionally, while the study captures differences between microfirms and SMEs, it does not account for sector-specific variations in innovation and sustainability practices, which may influence the generalizability of the findings. Future research could explore how industry-specific factors, such as regulatory environments or market competition, impact the adoption of AI technologies and sustainability outcomes (Heimberger et al., 2024). Lastly, the study notes that the moderating effects of digital innovation strategies, while significant, are relatively small in magnitude. This suggests the need for further investigation into contextual factors, such as organizational culture, leadership, or external pressures that may influence the effectiveness of these strategies. Addressing these limitations would provide deeper insights into the complex dynamics of digital transformation and sustainability in European firms.

### 5.4. Conclusion

The findings of this study challenge the prevailing assumption of a seamless complementarity between the digital and socio-environmental transitions, exposing a substitution effect that disrupts the expected synergies of the twin transition. The results reveal that Digital innovation strategy negatively moderates the relationship between AI-based technological systems adoption and environmental and social sustainability. This contradiction underscores that when digitalization and sustainability are strategically planned together under a rigid framework, their integration does not necessarily reinforce but may, instead, weaken one another.

While AI adoption contributes positively to sustainability dimensions, the introduction of a structured digital strategy seems to diminish these benefits in MSMEs, particularly in relation to environmental and social sustainability. This finding aligns with the idea that the twin transition is not as twin as often portrayed; rather than progressing hand in hand, the two transitions may work at cross-purposes depending on strategic and managerial decisions. The evidence suggests that digital strategies, when overly focused on automation and control, may prioritize efficiency and competitiveness over ecological and social concerns, ultimately undermining sustainability goals.

The findings of this study question whether the so-called twin transition is truly a convergence of digital and socio-environmental transformations or, instead, a "meeting of strangers," where digitalization and sustainability follow divergent or even conflicting paths.

## CRediT authorship contribution statement

**Joan Torrent-Sellens:** Writing – review & editing, Writing – original draft, Validation, Supervision, Software, Resources, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Mihaela Enache-Zegheru:** Writing – review & editing, Writing – original draft, Validation, Software, Methodology, Investigation, Formal analysis, Data curation. **Pilar Ficapal-Cusí:** Writing – review & editing, Writing – original draft, Validation, Investigation, Formal analysis, Data curation, Conceptualization.

## Declaration of competing interest

None.

## Annexes

*Annex 1. . Descriptive statistics*

**Table A.1.1**
Constructs, items and values

| | Microfirms | | SMEs | | MSMEs | |
|---|---|---|---|---|---|---|
| | *Mean* | *SD* | *Mean* | *SD* | *Mean* | *SD* |
| *Economic innovation (ECINN) (0 to 4)* | 0.700 | 0.973 | 0.943 | 1.063 | 0.802 | 1.019 |
| A new or significantly improved product or service to the market (no: 0; yes: 1) | 0.24 | 0.428 | 0.30 | 0.460 | 0.27 | 0.442 |
| A new or significantly improved production process or method (no: 0; yes: 1) | 0.15 | 0.360 | 0.23 | 0.424 | 0.19 | 0.390 |
| A new organization of management or a new business model (no: 0; yes: 1) | 0.11 | 0.319 | 0.20 | 0.401 | 0.15 | 0.358 |
| A new way of selling your goods or services (no: 0; yes: 1) | 0.19 | 0.393 | 0.20 | 0.403 | 0.20 | 0.397 |
| *AI-based technological systems (AITS) (0 to 6)* | 1.064 | 1.180 | 1.629 | 1.417 | 1.302 | 1.315 |
| *AIAS (AI-based algorithms & software)* | 0.552 | 0.696 | 0.795 | 0.808 | 0.654 | 0.755 |
| Algorithms machine learning (no: 0; yes: 1) | 0.05 | 0.214 | 0.09 | 0.280 | 0.06 | 0.245 |
| Cloud computing (no: 0; yes: 1) | 0.42 | 0.493 | 0.53 | 0.499 | 0.47 | 0.499 |
| Big Data Analytics (no: 0; yes: 1) | 0.09 | 0.280 | 0.18 | 0.380 | 0.12 | 0.329 |
| *AIHI (AI-based hardware & infrastructure)* | 0.512 | 0.714 | 0.835 | 0.870 | 0.648 | 0.799 |
| Robotics (no: 0; yes: 1) | 0.04 | 0.195 | 0.12 | 0.328 | 0.07 | 0.263 |
| Smart devices (no: 0; yes: 1) | 0.20 | 0.400 | 0.33 | 0.471 | 0.26 | 0.436 |
| High speed infrastructure (no: 0; yes: 1) | 0.27 | 0.445 | 0.38 | 0.485 | 0.32 | 0.466 |
| *Social innovation (SOCINN) (0 to 1)* | | | | | | |
| Social innovations, such as new products, services or processes that have the aim of improving society (no: 0; yes: 1) | 0.16 | 0.364 | 0.21 | 0.408 | 0.18 | 0.384 |
| *Environmental innovation (ENVINN) (0 to 1)* | 0.18 | 0.383 | 0.27 | 0.443 | 0.22 | 0.412 |
| *An innovation with an environmental benefit, including innovations with an energy or resource efficiency benefit (no: 0; yes: 1)* | | | | | | |
| *Digital innovation strategy (DIS)* | 0.73 | 0.962 | 0.93 | 1.042 | 0.82 | 1.004 |
| ACT: Has a strategy or action plan to go digital q9.8 (no: 0; yes: 1) | 0.16 | 0.369 | 0.27 | 0.442 | 0.21 | 0.405 |
| GVI: Growth via innovation q7a2 (not mentioned: 0; yes: 1) | 0.29 | 0.445 | 0.35 | 0.447 | 0.32 | 0.466 |
| GVD: Growth via digitalization advancement q7a.5 (not mentioned: 0; yes: 1) | 0.25 | 0.434 | 0.30 | 0.458 | 0.27 | 0.446 |
| *Environmental sustainability (ENVSUS) (0 to 4)* | 1.78 | 1.40 | 2.08 | 1.38 | 1.91 | 1.40 |
| *Circular environmental sustainability (CIRCSUS)* | 1.03 | 0.815 | 1.20 | 0.782 | 1.10 | 0.806 |
| Recycling or reusing materials (no: 0; yes: 1) | 0.57 | 0.495 | 0.63 | 0.482 | 0.60 | 0.490 |
| Saving energy or switching to sustainable energy sources (no: 0; yes: 1) | 0.46 | 0.498 | 0.57 | 0.495 | 0.51 | 0.500 |
| *Product environmental sustainability (PRODSUS)* | 0.75 | 0.776 | 0.88 | 0.803 | 0.80 | 0.790 |
| Reducing consumption of or impact on natural resources (no: 0; yes: 1) | 0.46 | 0.499 | 0.53 | 0.499 | 0.49 | 0.500 |
| Developing sustainable products or services (no: 0; yes: 1) | 0.28 | 0.450 | 0.34 | 0.475 | 0.31 | 0.462 |
| *Economic sustainability (ECSUS)* | | | | | | |
| SGF: Forecast for Company Sales Growth (1: no growth plans or unsure; values from 1 to 4). | 2.12 | 1.019 | 2.24 | 0.950 | 2.17 | 0.992 |
| EGF: Forecast for Company Employee Growth (1: no growth plans or unsure; values from 1 to 4). | 1.72 | 0.969 | 1.85 | 0.903 | 1.77 | 0.944 |
| SUSPLA: Sustainability Plan - combining economic success with social and environmental sustainability (0: no or unsure, 1: no but will consider in the future, 2: in the process of implementation, 3: implemented). | 1,19 | 1.001 | 1.49 | 0.984 | 1.32 | 1.004 |
| *Social sustainability (SOCSUS) (0 to 4)* | 1.75 | 1.410 | 2.18 | 1.373 | 1.93 | 1.411 |
| *Internal social sustainability (INTSOCSUS)* | 1.06 | 0.823 | 1.27 | 0.767 | 1.14 | 0.806 |
| Improving working conditions of its employees (no: 0; yes: 1) | 0.63 | 0.483 | 0.76 | 0.426 | 0.68 | 0.465 |
| Engaging employees in the governance of the enterprise (no: 0; yes: 1) | 0.43 | 0.495 | 0.50 | 0.500 | 0.46 | 0.498 |
| *External social sustainability (EXTSOCSUS)* | 0.50 | 0.769 | 0.92 | 0.795 | 0.79 | 0.797 |
| Promoting and improving diversity and equality in the workplace (no: 0; yes: 1) | 0.47 | 0.499 | 0.60 | 0.490 | 0.52 | 0.499 |
| Evaluating the impact of your enterprise on society (no: 0; yes: 1) | 0.23 | 0.421 | 0.32 | 0.466 | 0.27 | 0.442 |

## Annex 2. Discriminant validity

**Table A.2.1**
Fornell-Larcker Criteria

| Latent variable | AITS | DIS | ECINN | ECSUS | ENVINN | ENVSUS | SOCINN | SOCSUS |
|---|---|---|---|---|---|---|---|---|
| Microfirms | | | | | | | | |
| AITS | *0.837* | | | | | | | |
| DIS | 0.278 | *1.000* | | | | | | |
| ECINN | 0.288 | 0.358 | *1.000* | | | | | |
| ECSUS | 0.252 | 0.170 | 0.296 | *0.743* | | | | |
| ENVINN | 0.196 | 0.182 | 0.283 | 0.149 | *1.000* | | | |
| ENVSUS | 0.284 | 0.249 | 0.285 | 0.210 | 0.315 | *0.877* | | |
| SOCINN | 0.189 | 0.208 | 0.392 | 0.181 | 0.242 | 0.221 | *1.000* | |
| SOCSUS | 0.336 | 0.302 | 0.326 | 0.250 | 0.240 | 0.550 | 0.264 | *0.886* |
| SMEs | | | | | | | | |
| AITS | *0.844* | | | | | | | |
| DIS | 0.366 | *0.737* | | | | | | |
| ECINN | 0.309 | 0.362 | *1.000* | | | | | |
| ECSUS | 0.231 | 0.153 | 0.232 | *0.713* | | | | |
| ENVINN | 0.260 | 0.218 | 0.282 | 0.171 | *1.000* | | | |
| ENVSUS | 0.377 | 0.333 | 0.302 | 0.216 | 0.354 | *0.872* | | |
| SOCINN | 0.204 | 0.218 | 0.320 | 0.160 | 0.245 | 0.237 | *1.000* | |
| SOCSUS | 0.375 | 0.367 | 0.300 | 0.208 | 0.250 | 0.551 | 0.276 | *0.879* |
| MSMEs | | | | | | | | |
| AITS | *0.846* | | | | | | | |
| DIS | 0.355 | *0.737* | | | | | | |
| ECINN | 0.314 | 0.381 | *1.000* | | | | | |
| ECSUS | 0.259 | 0.194 | 0.279 | *0.733* | | | | |
| ENVINN | 0.244 | 0.221 | 0.292 | 0.169 | *1.000* | | | |
| ENVSUS | 0.339 | 0.311 | 0.302 | 0.224 | 0.339 | *0.876* | | |
| SOCINN | 0.206 | 0.228 | 0.363 | 0.179 | 0.249 | 0.234 | *1.000* | |
| SOCSUS | 0.372 | 0.362 | 0.326 | 0.249 | 0.256 | 0.557 | 0.276 | *0.885* |

**Note:** The square root of the AVE is represented by the elements in italics. Correlations between variables are shown below the diagonal.

Table A.3.2Heterotrait-Monotrait Ratio (HTMT)

| Latent variable | AITS | DIS | ECINN | ECSUS | ENVINN | ENVSUS | SOCINN | SOCSUS |
|---|---|---|---|---|---|---|---|---|
| Microfirms | | | | | | | | |
| AITS | | | | | | | | |
| DIS | 0.530 | | | | | | | |
| ECINN | 0.380 | 0.496 | | | | | | |
| ECSUS | 0.439 | 0.353 | 0.390 | | | | | |
| ENVINN | 0.259 | 0.264 | 0.283 | 0.197 | | | | |
| ENVSUS | 0.447 | 0.426 | 0.337 | 0.330 | 0.375 | | | |
| SOCINN | 0.250 | 0.294 | 0.392 | 0.239 | 0.242 | 0.261 | | |
| SOCSUS | 0.520 | 0.514 | 0.382 | 0.388 | 0.281 | 0.768 | 0.310 | |
| SMEs | | | | | | | | |
| AITS | | | | | | | | |
| DIS | 0.591 | | | | | | | |
| ECINN | 0.400 | 0.467 | | | | | | |
| ECSUS | 0.389 | 0.250 | 0.310 | | | | | |
| ENVINN | 0.336 | 0.278 | 0.282 | 0.206 | | | | |
| ENVSUS | 0.583 | 0.498 | 0.360 | 0.309 | 0.425 | | | |
| SOCINN | 0.264 | 0.281 | 0.320 | 0.204 | 0.245 | 0.282 | | |
| SOCSUS | 0.577 | 0.549 | 0.357 | 0.312 | 0.297 | 0.786 | 0.327 | |
| MSMEs | | | | | | | | |
| AITS | | | | | | | | |
| DIS | 0.571 | | | | | | | |
| ECINN | 0.404 | 0.489 | | | | | | |
| ECSUS | 0.437 | 0.316 | 0.367 | | | | | |
| ENVINN | 0.314 | 0.281 | 0.292 | 0.213 | | | | |
| ENVSUS | 0.519 | 0.466 | 0.356 | 0.335 | 0.404 | | | |
| SOCINN | 0.265 | 0.293 | 0.363 | 0.231 | 0.249 | 0.276 | | |
| SOCSUS | 0.563 | 0.536 | 0.383 | 0.377 | 0.300 | 0.780 | 0.323 | |

*Note*: HTMT ratio with 95% confidence intervals based on 5000 subsamples.

## Annex 3. . Sustainability pathways (direct effects)

**Table A.3.1**
Sustainability pathways in European microfirms (direct effects)

| Endogenous variable | Structural path | Direct effect | t-Value | 95% CI | f2 |
|---|---|---|---|---|---|
| Environmental innovation (ENVINN) | | | | | |
| ($R^2 = 0.094$) | ECINN → ENVINN | 0.095 | 17.055*** | [0.086; 0.104]Sig. | 0.062 |
| | AITS → ENVINN | 0.048 | 9.557*** | [0.040; 0.056]Sig. | 0.016 |
| Social innovation (SOCINN) | | | | | |
| (R2 = 0.160) | ECINN → SOCINN | 0.134 | 24.624*** | [0.125; 0.142]Sig. | 0.148 |
| | AITS → SOCINN | 0.030 | 6.223*** | [0.022; 0.038]Sig. | 0.008 |
| AI-based technological systems (AITS) | | | | | |
| (R2 = 0.083) | ECINN → AITS | 0.288 | 23.360*** | [0.268; 0.308]Sig. | 0.090 |
| Environmental sustainability (ENVSUS) | | | | | |
| (R2 = 0.193) | AITS → ENVSUS | 0.218 | 13.517*** | [0.191; 0.244]Sig. | 0.028 |
| | ENVINN → ENVSUS | 0.572 | 19.791*** | [0.525; 0.620]Sig. | 0.054 |
| | ECINN → ENVSUS (H1b) | 0.127 | 10.250*** | [0.107; 0.147]Sig. | 0.016 |
| | DIS X AITS → ENVSUS (H4b) | −0.146 | 5.204*** | [-0192; −0.101]Sig. | 0.004 |
| Economic sustainability (ECSUS) | | | | | |
| (R2 = 0.123) | ECINN → ECSUS (H1a) | 0.219 | 17.944*** | [0.198; 0.238]Sig. | 0.045 |
| | AITS → ECSUS | 0.138 | 8.330*** | [0.110; 0.165]Sig. | 0.010 |
| | DIS X AITS → ECSUS (H4a) | 0.069 | 2.339*** | [0.021; 0.018]Sig. | 0.001 |
| Social sustainability (SOCSUS) | | | | | |
| (R2 = 0.221) | AITS → SOCSUS | 0.283 | 17.875*** | [0.258; 0.310]Sig. | 0.048 |
| | SOCINN → SOCSUS | 0.344 | 10.964*** | [0.292; 0.395]Sig. | 0.017 |
| | ECINN → SOCSUS (H1c) | 0.144 | 11.544*** | [0.124; 0.164]Sig. | 0.020 |
| | DIS X AITS → SOCSUS (H4c) | −0.192 | 7.350*** | [-0.235; −0.149]Sig. | 0.007 |

Note. ***$p < 0.001$. R2 coefficient of determination; f2 effect size.

Table A.3.2Sustainability pathways in European SMEs (direct effects)

| Endogenous variable | Structural path | Direct effect | t-Value | 95% CI | f2 |
|---|---|---|---|---|---|
| Environmental innovation (ENVINN) | | | | | |
| ($R^2 = 0.113$) | ECINN → ENVINN | 0.099 | 14.790*** | [0.088; 0.110]Sig. | 0.051 |
| | AITS → ENVINN | 0.085 | 12.976*** | [0.073; 0.095]Sig. | 0.037 |
| Social innovation (SOCINN) | | | | | |
| ($R^2 = 0.115$) | ECINN → SOCINN | 0.116 | 17.622*** | [0.105; 0.127]Sig. | 0.083 |
| | AITS → SOCINN | 0.047 | 7.806*** | [0.037; 0.057]Sig. | 0.014 |
| AI-based technological systems (AITS) | | | | | |
| ($R^2 = 0.095$) | ECINN → AITS | 0.309 | 23.089*** | [0.286; 0.330]Sig. | 0.105 |
| Environmental sustainability (ENVSUS) | | | | | |
| ($R^2 = 0.258$) | AITS → ENVSUS | 0.306 | 17.355*** | [0.275; 0.333]Sig. | 0.052 |
| | ENVINN → ENVSUS | 0.515 | 18.431*** | [0.469; 0.561]Sig. | 0.062 |
| | ECINN → ENVSUS (H1b) | 0.111 | 8.274*** | [0.088; 0.133]Sig. | 0.013 |
| | DIS X AITS → ENVSUS (H4b) | −0.173 | 6.529*** | [-0.218; −0.131]Sig. | 0.007 |
| Economic sustainability (ECSUS) | | | | | |
| ($R^2 = 0.083$) | ECINN → ECSUS (H1a) | 0.169 | 11.625*** | [0.144; 0.192]Sig. | 0.026 |
| | AITS → ECSUS | 0.177 | 8.264*** | [0.140; 0.211]Sig. | 0.014 |
| | DIS X AITS → ECSUS (H4a) | −0.020 | 0.671 | [-0.068; 0.029]N.S. | 0.000 |
| Social sustainability (SOCSUS) | | | | | |
| ($R^2 = 0.247$) | AITS → SOCSUS | 0.338 | 18.012*** | [0.306; 0.368]Sig. | 0.063 |
| | SOCINN → SOCSUS | 0.357 | 11.421*** | [0.305; 0.409]Sig. | 0.025 |
| | ECINN → SOCSUS (H1c) | 0.105 | 7.829*** | [0.083; 0.128]Sig. | 0.011 |
| | DIS X AITS → SOCSUS (H4c) | −0.219 | 8.370*** | [-0.261; −0.176]Sig. | 0.012 |

*Note.* ***$p < 0.001$. $R^2$ coefficient of determination; $f^2$ effect size.

**Table A.3.3**
Sustainability pathways in European MSMEs (direct effects)

| Endogenous variable | Structural path | Direct effect | t-Value | 95% CI | f2 |
|---|---|---|---|---|---|
| Environmental innovation (ENVINN) | | | | | |
| ($R^2$ = 0.111) | ECINN → ENVINN | 0.098 | 22.891*** | [0.091; 0.105] Sig. | 0.058 |
| | AITS → ENVINN | 0.070 | 16.694*** | [0.063; 0.077] Sig. | 0.029 |
| Social innovation (SOCINN) | | | | | |
| ($R^2$ = 0.141) | ECINN → SOCINN | 0.127 | 30.216*** | [0.120; 0.134] Sig. | 0.115 |
| | AITS → SOCINN | 0.039 | 10.167*** | [0.033; 0.046] Sig. | 0.011 |
| AI-based technological systems (AITS) | | | | | |
| ($R^2$ = 0.098) | ECINN → AITS | 0.314 | 35.004*** | [0.299; 0.328] Sig. | 0.109 |
| Environmental sustainability (ENVSUS) | | | | | |
| ($R^2$ = 0.228) | AITS → ENVSUS | 0.260 | 21.626*** | [0.240; 0.280] Sig. | 0.038 |
| | ENVINN → ENVSUS | 0.544 | 27.088*** | [0.510; 0.577] Sig. | 0.057 |
| | ECINN → ENVSUS (H1b) | 0.120 | 13.074*** | [0.105; 0.135] Sig. | 0.015 |
| | DIS X AITS → ENVSUS (H4b) | −0.152 | 7.895*** | [-0.184; −0.122] Sig. | 0.005 |
| Economic sustainability (ECSUS) | | | | | |
| ($R^2$ = 0.113) | ECINN → ECSUS (H1a) | 0.203 | 21.917*** | [0.188; 0.218] Sig. | 0.038 |
| | AITS → ECSUS | 0.176 | 13.535*** | [0.154; 0.197] Sig. | 0.015 |
| | DIS X AITS → ECSUS (H4a) | −0.000 | 0.020 | [-0.034; 0.034] N.S. | 0.000 |
| Social sustainability (SOCSUS) | | | | | |
| ($R^2$ = 0.245) | AITS → SOCSUS | 0.322 | 26.929*** | [0.302; 0.341] Sig. | 0.060 |
| | SOCINN → SOCSUS | 0.350 | 16.083*** | [0.315; 0.386] Sig. | 0.020 |
| | ECINN → SOCSUS (H1c) | 0.129 | 14.418*** | [0.114; 0.143] Sig. | 0.016 |
| | DIS X AITS → SOCSUS (H4c) | −0.207 | 11.615*** | [-0.236; −0.178] Sig. | 0.010 |

Note. ***$p < 0.001$. R2 coefficient of determination; f2 effect size.

## Annex 4. . Sustainability pathways (mediation effects)

**Table A.4.1**
Sustainability pathways for European firms, by country (mediation effects)

| Mediation effect | Coefficient | t-Value | 95% CI | | Interpretation |
|---|---|---|---|---|---|
| | | | 5% | 95% | |
| Microfirms | | | | | |
| AITS → ENVINN → ENVSUS | 0.027 | 8.741 | 0.023 | 0.033 | Partial mediation |
| AITS → SOCINN →SOCSUS | 0.010 | 5.546 | 0.008 | 0.014 | Partial mediation |
| ECINN → ENVINN →ENVSUS (H2a) | 0.054 | 12.905 | 0.048 | 0.062 | Partial mediation |
| ECINN →SOCINN →SOCSUS (H2b) | 0.046 | 9.909 | 0.039 | 0.054 | Partial mediation |
| ECINN →AITS →ECSUS (H3a) | 0.040 | 7.869 | 0.032 | 0.048 | Partial mediation |
| ECINN →AITS →ENVINN (H3b) | 0.014 | 8.767 | 0.011 | 0.017 | Partial mediation |
| ECINN →AITS →ENVSUS (H3c) | 0.063 | 11.475 | 0.054 | 0.072 | Partial mediation |
| ECINN →AITS →SOCINN | 0.009 | 6.002 | 0.006 | 0.011 | Partial mediation |
| ECINN →AITS →SOCSUS | 0.082 | 13.741 | 0.072 | 0.092 | Partial mediation |
| ECINN →AITS → ENVINN →ENVSUS | 0.008 | 8.102 | 0.006 | 0.010 | Partial mediation |
| ECINN →AITS →SOCINN →SOCSUS | 0.003 | 5.411 | 0.002 | 0.004 | Partial mediation |
| SMEs | | | | | |
| AITS → ENVINN → ENVSOC | 0.044 | 10.692 | 0.037 | 0.050 | Partial mediation |
| AITS → ENVINN → ENVSUS | 0.017 | 6.690 | 0.013 | 0.021 | Partial mediation |
| AITS → SOCINN →SOCSUS | 0.051 | 11.572 | 0.044 | 0.059 | Partial mediation |
| ECINN → ENVINN →ENVSUS (H2a) | 0.041 | 9.575 | 0.035 | 0.049 | Partial mediation |
| ECINN →SOCINN →SOCSUS (H2b) | 0.055 | 7.809 | 0.043 | 0.066 | Partial mediation |
| ECINN →AITS →ECSUS (H3a) | 0.026 | 11.202 | 0.022 | 0.030 | Partial mediation |
| ECINN →AITS →ENVINN (H3b) | 0.094 | 13.631 | 0.083 | 0.106 | Partial mediation |
| ECINN →AITS →ENVSUS (H3c) | 0.015 | 7.304 | 0.011 | 0.018 | Partial mediation |
| ECINN →AITS →SOCINN | 0.104 | 13.728 | 0.092 | 0.117 | Partial mediation |
| ECINN →AITS →SOCSUS | 0.013 | 9.720 | 0.011 | 0.016 | Partial mediation |
| ECINN →AITS → ENVINN →ENVSUS | 0.005 | 6.398 | 0.004 | 0.007 | Partial mediation |
| ECINN →AITS →SOCINN →SOCSUS | 0.044 | 10.692 | 0.037 | 0.050 | Partial mediation |
| MSMEs | | | | | |
| AITS → ENVINN → ENVSOC | 0.038 | 14.532 | 0.034 | 0.042 | Partial mediation |
| AITS → ENVINN → ENVSUS | 0.014 | 8.801 | 0.011 | 0.016 | Partial mediation |
| AITS → SOCINN →SOCSUS | 0.053 | 17.344 | 0.048 | 0.058 | Partial mediation |
| ECINN → ENVINN →ENVSUS (H2a) | 0.044 | 14.045 | 0.039 | 0.050 | Partial mediation |
| ECINN →SOCINN →SOCSUS (H2b) | 0.055 | 12.723 | 0.048 | 0.062 | Partial mediation |
| ECINN →AITS →ECSUS (H3a) | 0.022 | 14.774 | 0.019 | 0.024 | Partial mediation |
| ECINN →AITS →ENVINN (H3b) | 0.082 | 17.860 | 0.074 | 0.089 | Partial mediation |
| ECINN →AITS →ENVSUS (H3c) | 0.012 | 9.743 | 0.010 | 0.014 | Partial mediation |
| ECINN →AITS →SOCINN | 0.101 | 20.675 | 0.093 | 0.109 | Partial mediation |
| ECINN →AITS →SOCSUS | 0.012 | 13.231 | 0.010 | 0.013 | Partial mediation |
| ECINN →AITS → ENVINN →ENVSUS | 0.004 | 8.552 | 0.004 | 0.005 | Partial mediation |
| ECINN →AITS →SOCINN →SOCSUS | 0.038 | 14.532 | 0.034 | 0.042 | Partial mediation |

*Note.* ***$p < 0.001$.

## Data availability

Data will be made available on request.

## References


Adams, R., Jeanrenaud, S., Bessant, J., Denyer, D., & Overy, P. (2016). Sustainability-oriented innovation: A systematic review. *International Journal of Management Reviews, 18*(2), 180–205.

Agrawal, A., Gans, J., & Goldfarb, A. (2019). Economic policy for artificial intelligence. In J. Lerner, & S. Stern (Eds.), *Innovation policy and the economy* (pp. 139–159). University of Chicago Press and NBER.

Agrawal, A., Gans, J., & Goldfarb, A. (2022). From prediction to transformation. *Harvard Business Review, 100*(11/12), 100–109.

Aguilera, R. V., De Massis, A., Fini, R., Vismara, S., & Organizational, S. (2024). goals, outcomes, and the assessment of performance: Reconceptualizing success in management studies. *J. Manage. Stud., 61*(1), 1–36.

Arranz, C. F., Arroyabe, M. F., Arranz, N., & de Arroyabe, J. C. F. (2023). Digitalisation dynamics in SMEs: An approach from systems dynamics and artificial intelligence. *Technol. Forecast. Soc. Chang, 196*, Article 122880.

Arroyabe, M. F., Arranz, C. F., de Arroyabe, I. F., & de Arroyabe, J. C. F. (2024). The effect of IT security issues on the implementation of industry 4.0 in SMEs: Barriers and challenges. *Technol. Forecast. Soc. Chang, 199*, Article 123051.

Babina, T., Fedyk, A., He, A., & Hodson, J. (2024). Artificial intelligence, firm growth, and product innovation. *Journal of Financial Economics, 151*, Article 103745.

Bari, N., Chimhundu, R., & Chan, K. C. (2022). Dynamic capabilities to achieve corporate sustainability: A roadmap to sustained competitive advantage. *Sustainability, 14*(3), 1531.

Barney, J. B. (1991). The resource-based view of strategy: Origins, implications, and prospects. *Journal of Management, 17*, 97–211.

Barney, J. B. (1996). The resource-based theory of the firm. *Organ. Sci., 7*, 469.

Barney, J. B. (2001). Resource-based theories of competitive advantage: A ten-year retrospective on the resource-based view. *Journal of Management, 27*, 643–650.

Benitez, G. B., Ghezzi, A., & Frank, A. G. (2023). When technologies become Industry 4.0 platforms: Defining the role of digital technologies through a boundary-spanning perspective. *International Journal of Production Economics, 260*, Article 108858.

Bhadra, K. V., Kamalanabhan, T. J., & Singh, S. K. (2024). Evolution of dynamic capabilities for business sustainability performance: Evidence from the Indian manufacturing sector, Bus. Strateg. *Environ.* https://doi.org/10.1002/bse.3767

Brynjolfsson, E., & McAfee, A. (2014). *The second machine age: Work, progress, and prosperity in a time of brilliant technologies* (1st ed.). New York: W.W. Norton & Company.

Brynjolfsson, E., Wang, J. W., & McElheran, K. (2021). The power of prediction: Predictive analytics, workplace complements, and business performance. *Bus. Econ., 56*(4), 217–239.

Buzzao, G., & Rizzi, F. (2021). On the conceptualization and measurement of dynamic capabilities for sustainability: Building theory through a systematic literature review. *Bus. Strateg. Environ., 30*(1), 135–175.

Cannavacciuolo, L., Ferraro, G., Ponsiglione, C., Primario, S., & Quinto, I. (2023). Technological innovation-enabling industry 4.0 paradigm: A systematic literature review. *Technovation, 124*, Article 102733.

Cappa, F., Oriani, R., Peruffo, E., & McCarthy, I. (2021). Big data for creating and capturing value in the digitalized environment: Unpacking the effects of volume, variety, and veracity on firm performance. *J. Prod. Innov. Manag., 38*, 49–67.

Castillo Esparza, M. M. G. C., Madrid-Guijarro, A., & Maldonado-Guzman, G. (2024). Greening Mexican manufacturing: Examining the role of SMEs in environmental preservation through green business strategies, eco-innovation, and corporate social responsibility. *Sustainable Development*, 1–16.

Chen, P., Chu, Z., & Zhao, M. (2024). The road to corporate sustainability: The importance of artificial intelligence. *Technology in Society, 76*, Article 102440.

Chen, X., Kurdve, M., Johansson, B., & Despeisse, M. (2023). Enabling the twin transitions: Digital technologies support environmental sustainability through lean principles. *Sustain. Prod. Consump., 38*, 13–27.

Chhillar, D., & Aguilera, R. V. (2022). An eye for artificial intelligence: Insights into the governance of artificial intelligence and vision for future research. *Business & Society, 61*(5), 1197–1241.

Collini, L., & Hausemer, P. (2023). Place-based pathways for the twin transition: The role of systemic change agents. *Competitiveness Review*. https://doi.org/10.1108/CR-03-2023-0060

Crafts, N. (2021). Artificial intelligence as a general-purpose technology: An historical perspective. *Oxf. Rev. Econ. Policy, 37*(3), 521–536.

Dangelico, R. M., & Pontrandolfo, P. (2015). Being 'green and competitive': The impact of environmental actions and collaborations on firm performance. *Bus. Strateg. Environ., 24*(6), 413–430.

Dangelico, R. M., Pujari, D., & Pontrandolfo, P. (2017). Green product innovation in manufacturing firms: A sustainability-oriented dynamic capability perspective. *Bus. Strateg. Environ., 26*(4), 490–506.

de Sousa Jabbour, A. B. L., Jabbour, C. J. C., Foropon, C., & Godinho Filho, M. (2018). When titans meet–can industry 4.0 revolutionise the environmentally-sustainable manufacturing wave? The role of critical success factors. *Technol. Forecast. Soc. Chang, 132*, 18–25.

Díaz-Chao, Á., Ficapal-Cusí, P., & Torrent-Sellens, J. (2021). Environmental assets, industry 4.0 technologies and firm performance in Spain: A dynamic capabilities path to reward sustainability. *Journal of Cleaner Production, 281*, Article 125264.

Diodato, D., Huergo, E., Moncada-Paternò-Castello, P., Rentocchini, F., & Timmermans, B. (2023). Introduction to the special issue on "the twin (digital and green) transition: Handling the economic and social challenges. *Ind. Innov., 30*(7), 755–765.

Dubey, R., Gunasekaran, A., Childe, S. J., Bryde, D. J., Giannakis, M., Foropon, C., et al. (2020). Big data analytics and artificial intelligence pathway to operational performance under the effects of entrepreneurial orientation and environmental dynamism: A study of manufacturing organisations. *International Journal of Production Economics, 226*, Article 107599.

Dubey, R., Gunasekaran, A., Childe, S. J., Papadopoulos, T., Luo, Z., Wamba, S. F., & Roubaud, D. (2019). Can big data and predictive analytics improve social and environmental sustainability? *Technol. Forecast. Soc. Chang., 144*, 534–545.

Dwivedi, Y. K., Hughes, L., Ismagilova, E., Aarts, G., Coombs, C., Crick, T., et al. (2021). Artificial intelligence (AI): Multidisciplinary perspectives on emerging challenges, opportunities, and agenda for research, practice and policy. *Int. J. Inf. Manage., 57*, Article 101994.

Dwivedi, Y. K., Hughes, L., Kar, A. K., Baabdullah, A. M., Grover, P., Abbas, R., et al. (2022). Climate change and COP26: Are digital technologies and information management part of the problem or the solution? An editorial reflection and call to action. *Int. J. Inf. Manage., 63*, Article 102456.

Eikelenboom, M., & de Jong, G. (2019). The impact of dynamic capabilities on the sustainability performance of SMEs. *Journal of Cleaner Production, 235*, 1360–1370.

Elkington, J. (1997). *Cannibals with forks: The triple bottom line of 21st century business*. Oxford: Capstone.

Ellström, D., Holtström, J., Berg, E., & Josefsson, C. (2022). Dynamic capabilities for digital transformation. *J. Strateg. Manag., 15*(2), 272–286.

Epstein, M. J., Buhovac, A. R., & Yuthas, K. (2015). Managing social, environmental and financial performance simultaneously. *Long Range Planning, 48*(1), 35–45.

Eurofound. (2020). *Game-changing technologies: Transforming production and employment in Europe*. Publications Office of the European Union. Available at: http://eurofound.link/ef19047.

European Commission. (2020). *SMEs, start-ups, scale-ups and entrepreneurship, 2244/FL486*. Available at: https://europa.eu/eurobarometer/surveys/detail/2244.

European Commission. (2022). *2022 strategic foresight report. Twinning the green and digital transitions in the new geopolitical context. Communication from the Commission to the European Parliament and the Council, COM (2022) 289 final*. Available at: https://ec.europa.eu/info/files/strategic-foresight-report-2022-en.

Faludi, J. (2023). How to create social value through digital social innovation? Unlocking the potential of the social value creation of digital start-up. *J. Soc. Entrep., 14*(1), 73–90.

Ferreira, J. J., Fernandes, C. I., Veiga, P. M., & Caputo, A. (2022). The interactions of entrepreneurial attitudes, abilities and aspirations in the (twin) environmental and digital transitions? A dynamic panel data approach. *Technology in Society, 71*, Article 102121.

Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research, 18*(1), 39–48.

Fouquet, R., & Hippe, R. (2022). Twin transitions of decarbonisation and digitalisation: A historical perspective on energy and information in European economies. *Energy Res. Soc. Sci., 91*, Article 102736.

George, A. S. (2024). Bracing for the coming AI tsunami: Preparing the global workforce for displacement and inequality in the age of accelerating technological advancement. *2*, 126–146. https://doi.org/10.5281/zenodo.11668571

Ghisetti, C., & Rennings, K. (2014). Environmental innovations and profitability: How does it pay to be green? An empirical analysis on the German innovation survey. *Journal of Cleaner Production, 75*, 106–117.

Ghobakhloo, M. (2020). Industry 4.0, digitization, and opportunities for sustainability. *Journal of Cleaner Production, 252*, Article 119869.

Ghobakhloo, M., Iranmanesh, M., Grybauskas, A., Vilkas, M., & Petraitė, M. (2021). Industry 4.0, innovation, and sustainable development: A systematic review and a roadmap to sustainable innovation. *Bus. Strateg. Environ., 30*(8), 4237–4257.

Ghobakhloo, M., Vilkas, M., Stefanini, A., Grybauskas, A., Marcinkevicius, G., Petraite, M., & Sarvari, P. A. (2023). Developing capabilities underlying to Industry 4.0 design principles within the manufacturing context. *Journal of Manufacturing Technology Management, 34*(7), 1183–1207.

Ghosh, S., Hughes, M., Hodgkinson, I., & Hughes, P. (2022). Digital transformation of industrial businesses: A dynamic capability approach. *Technovation, 113*, Article 102414.

Goldfarb, A., Taska, B., & Teodoridis, F. (2023). Could machine learning be a general purpose technology? A comparison of emerging technologies using data from online job postings. *Res. Policy, 52*(1), Article 104653.

Grashof, N., & Kopka, A. (2023). Artificial intelligence and radical innovation: An opportunity for all companies? *Small Business Economics, 61*, 771–797.

Green, F., & Healy, N. (2022). How inequality fuels climate change: The climate case for a New Green Deal. *One Earth, 5*(6), 635–649.

Guandalini, I. (2022). Sustainability through digital transformation: A systematic literature review for research guidance. *Journal of Business Research, 148*, 456–471.

Gupta, S., Kumar, V., & Karam, E. (2020). New-age technologies-driven social innovation: What, how, where, and why? *Ind. Mark. Manage., 89*, 499–516.

Haefner, N., Wincent, J., Parida, V., & Gassmann, O. (2021). Artificial intelligence and innovation management: A review, framework, and research agenda. *Technol. Forecast. Soc. Chang., 162*, Article 120392.

Hair, J. F., Hult, G. T. M. T. M., Ringle, C. M., & Sarstedt, M. M. (2017). *A primer on partial least squares structural equation modeling PLS-SEM* (2on edition). Sage.

Heimberger, H., Horvat, D., & Schultmann, F. (2024). Exploring the factors driving AI adoption in production: A systematic literature review and future research agenda.

*Information Technology and Management*. https://doi.org/10.1007/s10799-024-00436-z

Hellemans, I., Porter, A. J., & Diriker, D. (2022). Harnessing digitalization for sustainable development: Understanding how interactions on sustainability-oriented digital platforms manage tensions and paradoxes. *Bus. Strateg. Environ., 31*(2), 668–683.

Henseler, J., Ringle, C. M., & Sarstedt, M. M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. *J. Acad. Mark. Sci., 43*(1), 115–135.

Hickel, J., & Kallis, G. (2020). Is green growth possible? New polit. *Economic Times, 25* (4), 469–486.

Kar, A. K., Choudhary, S. K., & Singh, V. K. (2022). How can artificial intelligence impact sustainability: A systematic literature review. *Journal of Cleaner Production, 376*, Article 134120.

Kopka, A., & Fornahl, D. (2024). Artificial intelligence and firm growth-catch-up processes of SMEs through integrating AI into their knowledge bases. *Small Business Economics, 62*(1), 63–85.

Krakowski, S., Luger, J., & Raisch, S. (2023). Artificial intelligence and the changing sources of competitive advantage. *Strateg. Manage. J., 44*(6), 1425–1452.

Lee, Y. S., Kim, T., Choi, S., & Kim, W. (2022). When does AI pay off? AI-adoption intensity, complementary investments, and R&D strategy. *Technovation, 118*, Article 102590.

Lu, Y. Z., Xu, C., Zhu, B. S., & Sun, Y. Q. (2023). Digitalization transformation and ESG performance: Evidence from China. *Bus. Strategy Environ.*. https://doi.org/10.1002/bse.3494

Mariani, M. M., Machado, I., Magrelli, V., & Dwivedi, Y. K. (2023). Artificial intelligence in innovation research: A systematic review, conceptual framework, and future research directions. *Technovation, 122*, Article 102623.

Martinelli, A., Mina, A., & Moggi, M. (2021). The enabling technologies of industry 4.0: Examining the seeds of the fourth industrial revolution. *Ind. Corp. Chang., 30*(1), 161–188.

Martínez-Caro, E., Cegarra-Navarro, J. G., & Alfonso-Ruiz, F. J. (2020). Digital technologies and firm performance: The role of digital organisational culture. *Technological Forecasting and Social Change, 154*, Article 119962.

Mehmood, K., Jabeen, F., Rashid, M., Alshibani, S. M., Lanteri, A., & Santoro, G. (2024). Unraveling the transformation: The three-wave time-lagged study on big data analytics, green innovation and their impact on economic and environmental performance in manufacturing SMEs. *Eur. J. Innov. Manag.*. https://doi.org/10.1108/EJIM-10-2023-0903

Mithani, M. A. (2017). Innovation and CSR - do they go well together? *Long Range Planning, 50*(6), 699–711.

Montresor, S., & Vezzani, A. (2023). Digital technologies and eco-innovation. Evidence of the twin transition from Italian firms. *Ind. Innov., 30*(7), 766–800.

Mousavi, S., Bossink, B., & van Vliet, M. (2018). Dynamic capabilities and organizational routines for managing innovation towards sustainability. *Journal of Cleaner Production, 203*, 224–239.

Muench, S., Stoermer, E., Jensen, K., Asikainen, T., Salvi, M., & Scapolo, F. (2022). Towards a green and digital future. *Key requirements for successful twin transitions in the European union, JCR science for policy report, EUR 31075*. Publications Office of the European Union.

Naudé, W. (2021). Artificial intelligence: Neither utopian nor apocalyptic impacts soon. *Econ. Innov. New Technol., 30*(1), 1–23.

Ning, J., Jiang, X., & Luo, J. (2023). Relationship between enterprise digitalization and green innovation: A mediated moderation model. *J. Innov. Knowl., 8*, Article 100326.

Nishant, R., Kennedy, M., & Corbett, J. (2020). Artificial intelligence for sustainability: Challenges, opportunities, and a research agenda. *Int. J. Inf. Manage., 53*, Article 102104.

Nuccio, M., & Guerzoni, M. (2019). Big data: Hell or heaven? Digital platforms and market power in the data-driven economy. *Compet. Chang, 23*(3), 312–328.

Opazo-Basáez, M., Monroy-Osorio, J. C., & Marić, J. (2024). Evaluating the effect of green technological innovations on organizational and environmental performance: A treble innovation approach. *Technovation, 129*, Article 102885.

Ortega-Gras, J. J., Bueno-Delgado, M. V., Cañavate-Cruzado, G., & Garrido-Lova, J. (2021). Twin transition through the implementation of industry 4.0 technologies: Desk-research analysis and practical use cases in Europe. *Sustainability, 13*(24), Article 13601.

Ozusaglam, S., Kesidou, E., & Wong, C. Y. (2018). Performance effects of complementarity between environmental management systems and environmental technologies. *International Journal of Production Economics, 197*, 112–122.

Paiho, S., Wessberg, N., Dubovik, M., Lavikka, R., & Naumer, S. (2023). Twin transition in the built environment–policy mechanisms, technologies and market views from a cold climate perspective. *Sust. Cities Soc., 98*, Article 104870.

Podsakoff, P. M., Podsakoff, N. P., Williams, L. J., Huang, C., & Yang, J. (2024). Common method bias: It's bad, it's complex, it's widespread, and it's not easy to fix, Annu. Rev. Organ. Psychol. *Organ. Behav., 11*, 17–61.

Porter, M. E., & Kramer, M. R. (2011). Creating shared value. *Harvard Business Review, 89* (1–2), 62–77.

Porter, M. E., & van der Linde, C. (1995). Toward a new conception of the environment-competitiveness relationship. *The Journal of Economic Perspectives, 9*(4), 97–118.

Raj, A., & Jeyaraj, A. (2023). Antecedents and consequents of industry 4.0 adoption using technology, organization and environment (TOE) framework: A meta-analysis. *Annals of Operations Research, 322*(1), 101–124.

Ramanathan, R., He, Q., Black, A., Ghobadian, A., & Gallear, D. (2017). Environmental regulations, innovation and firm performance: A revisit of the porter hypothesis. *Journal of Cleaner Production, 155*, 79–92.

Rehman, S. U., Giordino, D., Zhang, Q., & Alam, G. M. (2023). Twin transitions & industry 4.0: Unpacking the relationship between digital and green factors to determine green competitive advantage. *Technology in Society, 73*, Article 102227.

Rexhäuser, S., & Rammer, C. (2014). Environmental innovations and firm profitability: Unmasking the porter hypothesis. *Environmental and Resource Economics, 57*(1), 145–167.

Ringle, C. M., Wende, S., & Becker, J. M. (2015). SmartPLS 3. Bönningstedt: SmartPLS. http://www.smartpls.com.

Rogers, E. (2003). *Diffusion of innovations* (5th ed.). Free Press.

Roldán, J. L., & Sánchez-Franco, M. J. (2012). Variance-based structural equation modelling: Guidelines for using partial least squares in information systems research. *Research Methodologies, Innovations and Philosophies in Software Systems Engineering and Information Systems*. https://doi.org/10.4018/978-1-4666-0179-6.ch010

Saha, R., Shashi, C., Singh, R., & Dahiya, R. (2020). Effect of ethical leadership and corporate social responsibility on firm performance: A systematic review. *Corporate Social Responsibility and Environmental Management, 27*(2), 409–429.

Sharma, R., Lopes de Sousa Jabbour, A. B., Jain, V., & Shishodia, A. (2020). The role of digital technologies to unleash a green recovery: Pathways and pitfalls to achieve the European green Deal. *J. Enterp. Inf. Manag., 35*(1), 266–294.

Shrivastava, P. (1995). Environmental technologies and competitive advantage. *Strateg. Manage. J., 16*(S1), 183–200.

Singer, M. (2018). *Climate change and social inequality: The health and social costs of global warming*. Routledge.

Singh, S. K., Giudice, M., del Chierici, R., & Graziano, D. (2020). Green innovation and environmental performance: The role of green transformational leadership and green human resource management. *Technol. Forecast. Soc. Chang., 150*, Article 119762.

Slameršak, A., Kallis, G., O'Neill, D. W., & Hickel, J. (2024). Post-growth: A viable path to limiting global warming to 1.5° C. *One Earth, 7*(1), 44–58.

Srivastava, R., Prashar, A., Iyer, S. V., & Gotise, P. (2022). Insurance in the industry 4.0 environment: A literature review, synthesis, and research agenda. *Australian Journal of Management*, Article 03128962221132458.

Teece, D. J. (2007). Explicating dynamic capabilities: The nature and microfoundations of (sustainable) enterprise performance. *Strateg. Manage. J., 28*(13), 1319–1350.

Teece, D. J. (2014). The foundations of enterprise performance: Dynamic and ordinary capabilities in an (economic) theory of firms. *Acad. Manage. Perspect., 28*(4), 328–352.

Teece, D. J. (2016). Dynamic capabilities and entrepreneurial management in large organizations: Toward a theory of the (entrepreneurial) firm. *European Economic Review, 86*, 202–216.

Tekic, Z., & Tekic, A. (2024). Complex patterns of ICTs' effect on sustainable development at the national level: The triple bottom line perspective. *Technological Forecasting and Social Change, 198*, Article 122969.

Torrent-Sellens, J. (2024). Homo digitalis: Narrative for a new political economy of digital transformation and transition. *New Political Economy, 29*(1), 125–143.

Torrent-Sellens, J. (2024). Digital transition, data-and-tasks crowd-based economy, and the shared social progress: unveiling a new political economy from a European perspective. *Technology in Society, 79*, .102739.

Torrent-Sellens, J., Ficapal-Cusí, P., & Enache, M. (2023). Boosting environmental management: The mediating role of industry 4.0 between environmental assets and economic and social firm performance. *Bus. Strateg. Environ., 32*(1), 753–768.

Torres de Oliveira, R., Ghobakhloo, M., & Figueira, S. (2023). Industry 4.0 towards social and environmental sustainability in multinationals: Enabling circular economy, organizational social practices, and corporate purpose. *Journal of Cleaner Production*, Article 139712.

Venturini, F. (2022). Intelligent technologies and productivity spillovers: Evidence from the fourth industrial revolution. *J. Econ. Behav. Org., 194*, 220–243.

Wei, Z., & Sun, L. (2021). How to leverage manufacturing digitalization for green process innovation: An information processing perspective. *Ind. Manag. Data Syst., 121*, 1026–1044.

Yang, C. H. (2022). How artificial intelligence technology affects productivity and employment: Firm-level evidence from Taiwan. *Res. Policy, 51*(6), Article 104536.

Zhou, W., Zhuang, Y., & Chen, Y. (2024). How does artificial intelligence affect pollutant emissions by improving energy efficiency and developing green technology. *Energy Econ, 131*, Article 107355.