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Company Location, Business Environment and Digital Maturity as Drivers of Environmental Innovation in Business

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ABSTRACT

Environmental protection has emerged as a global priority in the contemporary context. As pivotal actors in the transition towards sustainable development, companies play a crucial role through the adoption of environmental innovations. This study investigates how organisational characteristics—specifically geographical location, business environment and digital maturity—influence the adoption of environmental innovations, employing machine learning models to develop a robust predictive framework. Although previous research has highlighted the relevance of these factors, their specific dynamics and interactions remain insufficiently explored. Drawing on data from Flash Eurobarometer 486, which comprises information from 16,365 firms across 27 EU Member States and 12 additional countries, this analysis examines how geographical context and internal capabilities shape environmental innovation performance, with particular attention given to the moderating role of firm size. The study leverages machine learning algorithms, including logistic regression, random forests and gradient boosting machines, to capture complex relationships and address challenges such as overfitting. The results demonstrate that location, business environment and digital maturity significantly influence environmental innovation. Moreover, company size moderates these relationships, either amplifying or attenuating their effects, thus providing a nuanced understanding of how firms can optimise their characteristics to advance sustainable practices. By integrating machine learning techniques into the analysis, this research contributes to the literature on environmental innovation by offering a systematic approach to identifying key drivers. These findings hold critical implications for policymakers and business leaders seeking to enhance sustainability through innovation.

1 | Introduction

The relentless pursuit of economic growth has driven global economies to intensify industrial activities (Mahmood et al. 2022; Sharif et al. 2023), often resulting in environmental degradation and increased pressure on natural resources. Since the Brundtland Report (1987) introduced the concept of sustainable development, there has been a growing adoption of environmentally responsible practices by institutions and companies alike. This paradigm shift has heightened social,

Abbreviations: AI, artificial intelligence; AUC, area under the ROC curve; CDFC, canonical discriminant function coefficients; CI, confidence intervals; EU, European Union; GBM, gradient boosting machines; IoT, Internet of Things; KNN, *K*-nearest neighbours; LDA, linear discriminant analysis; ML, machine learning; OECD, Organisation for Economic Co-operation and Development; PDP, partial dependence plots; R&D, research and development; ROC, receiver operating characteristic; SD, standard deviation; SME, small and medium enterprise; SVM, support vector machines.

political and academic attention towards sustainability, leading to the establishment of global frameworks for action. Notably, the United Nations 2030 Agenda and its sustainable development goals (SDGs) (United Nations, 2025) represent a global commitment to transforming production and consumption patterns towards more sustainable and resilient models. Against this backdrop, corporate social responsibility (CSR) has become a strategic mechanism that connects global sustainability objectives with firms' ethical and innovation-driven strategies (Morea et al. 2023; Cerchione et al. 2025). Beyond these institutional and market mechanisms, CSR serves as a conceptual and managerial bridge between external drivers—such as regulation, market dynamics and territorial context—and firms' internal ethical–strategic orientations. By integrating social and environmental considerations into decision-making, companies can translate external sustainability imperatives into concrete innovation practices. As highlighted by Morea et al. (2023), CSR constitutes a strategic approach that simultaneously integrates economic, social and environmental goals, acting as a catalyst for sustainable practices and circular economy models, particularly in resource-intensive sectors. In line with Cerchione et al. (2025), CSR aligns with the "Do No Significant Harm" (DNSH) principle and the European Union taxonomy for sustainable finance, ensuring that investment decisions and corporate strategies are oriented toward verifiable environmental and social impacts. Incorporating CSR as an ethical–strategic dimension thus helps to explain how companies internalise sustainability within their business models and how such integration reinforces social and environmental innovation processes.

Environmental innovations—or eco-innovations—have emerged as critical drivers for reducing the environmental impact of business activities (Dangelico et al. 2017; Darmandieu et al. 2022). These innovations encompass the development of novel products, processes or services that mitigate environmental risks, emissions and waste (Kotani and Kakinaka 2017).

Sustainable practices have increasingly become a strategic priority for businesses. Prior research has emphasised the role of organisational factors in fostering environmental innovation, yet adoption remains particularly challenging for small and medium-sized enterprises (SMEs) (Edu et al. 2024). Key barriers hindering eco-innovation in SMEs include limited awareness, scarce resources and insufficient support mechanisms (Madrid-Guijarro and Duréndez 2024). Nonetheless, these challenges also affect firms of all sizes, albeit to varying degrees.

Despite growing scholarly interest in eco-innovation within SMEs, empirical findings remain fragmented and often inconclusive. Moreover, many studies rely on conventional analytical frameworks that inadequately capture the complex interplay of multiple influencing factors. This fragmentation partly stems from the intrinsic heterogeneity of SMEs, which tend to exhibit more flexible organisational structures, heightened environmental sensitivity and more direct decision-making processes compared with larger firms (Crossley et al. 2021; Zartha Sossa et al. 2021).

Consequently, there is a pressing need for more integrated and methodologically sophisticated approaches to better understand the determinants of environmental innovation across diverse business contexts.

Unlike most prior studies that analyse environmental innovation from a single perspective—circular economy and SMEs (Darmandieu et al. 2022); R&D cooperations and environmental innovation (Dimakopoulou et al. 2023); resource efficiency in SMEs for sustainable practices (Edu et al. 2024); rural–urban comparison (Galliano et al. 2023); environmental innovation on mergers and acquisitions (Hussain et al. 2024)—this research adopts an integrative approach, simultaneously considering firm location, business environment and digital maturity to reveal complex interactions that shape eco-innovation across diverse territorial contexts.

To address these gaps, this study offers several key contributions. First, it incorporates firm geographical location—a variable seldom examined in prior research—by differentiating between rural and urban contexts to assess their influence on environmental innovation. Second, it integrates business environment and digital maturity factors, providing a comprehensive perspective on eco-innovation drivers. Third, it explores the moderating effect of firm size, a crucial dimension, particularly for SMEs and start-ups. Lastly, the study leverages a broad spectrum of machine learning (ML) algorithms, surpassing traditional methodologies to uncover complex data patterns with enhanced precision. Collectively, these contributions aim to bridge existing gaps in the literature and strengthen the empirical basis for sustainable business policy and strategy development.

Aligned with the SDGs, this research directly contributes to SDG 8.4, which promotes the progressive improvement of global resource efficiency in consumption and production. By identifying the factors that drive environmental innovation, the study also supports SDG 9 by fostering innovative and sustainable business practices and SDG 12 by providing valuable insights for transitioning towards more responsible production models. Furthermore, by considering the role of SMEs and their territorial context, the research offers relevant evidence for the formulation of differentiated policies that promote sustainable and inclusive economic growth in diverse settings, in line with the crosscutting approach proposed by the 2030 Agenda.

A key and distinctive contribution of this research lies in the innovative methodology employed, representing an advance over previous studies. While prior research has primarily relied on conventional statistical methods, the use of ML algorithms to explore the determinants of environmental innovation remains limited. By applying ML techniques to a large, multicountry dataset, this study surpasses traditional approaches, enabling the detection of complex patterns and interactions that were previously overlooked. In doing so, it addresses critical limitations of conventional models, such as their inability to handle complexity, dependence on sample characteristics and reliance on predefined functional forms, thereby reinforcing the originality and value of the methodological approach.

The analysis employs a diverse set of ML algorithms, including logistic regression, linear discriminant analysis (LDA), decision trees, random forests, support vector machines (SVMs), gradient boosting (GB) machines, naïve Bayes, *k*-nearest neighbours (KNN) and artificial neural networks (ANNs). These techniques allow for a more advanced and nuanced examination of variable relationships while minimising risks such as overfitting. This methodological framework not only facilitates a systematic and robust understanding of the drivers of eco-innovation but also provides a comprehensive framework for their identification, considering both firm-specific characteristics and geographical factors, thus highlighting the novelty and significance of this study's contribution.

The analysis is based on an extensive and diverse dataset from Flash Eurobarometer 486, conducted by the European Union. This dataset encompasses information from 27 EU Member States and 12 additional countries, collected through telephone interviews with key managers of 16,365 companies between 19 February and 5 May 2020. Such a broad and representative sample provides significant insights into environmental innovation across a range of business contexts.

Despite growing academic interest in eco-innovation, there is a notable gap in research that jointly examines the influence of firm location, business environment and digital maturity on environmental innovation—particularly when moderated by firm size. In this context, the study aims to address the following research questions:

- How do firm location, business environment and digital maturity influence a firm's environmental innovation?
- Does firm size moderate these relationships?

In summary, this article primarily aims to analyse the effect of location (rural or urban), the business environment and digital maturity on environmental innovation in firms—particularly SMEs and start-ups—and to assess how firm size moderates these relationships.

The article is structured into five sections. Following the "Introduction," the "Literature Review and Hypotheses" explores the relationship between environmental innovation and firms, outlining key theoretical foundations. The "Research Methodology" describes the dataset, the ML algorithms employed and the evaluation metrics used in the analysis. The "Results" section presents the findings, emphasising the performance of the algorithms and the influence of various variables. Finally, the "Discussion" provides a comprehensive summary of the results and examines their theoretical and practical implications for fostering eco-innovation in firms.

2 | Literature Review and Hypotheses

2.1 | Business Localisation and Environmental Innovation

Environmental innovation developed by a company is closely linked to its geographical location. The rural or urban context significantly influences the challenges and opportunities firms face when adopting environmental innovations (Malerba 2010). Recent studies underscore the importance of location in fostering eco-innovation (Horbach and Rammer 2018; D'Agostino and Moreno 2019). Although this study employs a traditional definition of rural and urban areas to examine the relationship with environmental innovation, it is important to recognise that, in various global regions—particularly in Asian and developing countries—definitions and dynamics related to business location can be more complex and multidimensional. Therefore, while a simplified approach is adopted here for analytical purposes, future research could advance this line of inquiry by incorporating more specific institutional and contextual dimensions.

Several contextual factors shape how location influences a firm's environmental awareness: (1) proximity to and reliance on natural resources, (2) sensitivity to environmental changes, (3) traditions of green practices and (4) access to sustainability programmes and public policies.

For firms situated in natural environments, both their direct connection to the environment and their reliance on local resources play pivotal roles. Companies located in rural areas often depend heavily on natural resources such as land and water, receiving immediate feedback on the environmental impact of their operations, fostering a heightened sense of responsibility (Battisti and Perry 2011). In sectors such as agriculture, livestock or forestry, sustainability, soil quality, water availability and biodiversity are essential for business continuity. These factors encourage the adoption of sustainable practices, albeit with associated challenges. However, some scholars argue that rural areas—often perceived as low-density and non-innovative territories—have received limited academic attention (Galliano et al. 2023).

Nonetheless, industrial specialisation within a territory, whether rural or urban, can create favourable conditions for eco-innovation (Hansen and Coenen 2015). Urban environments, in particular, often benefit from industrial agglomerations that facilitate knowledge exchange and the diffusion of ideas, which are critical for environmental innovation processes (Ghisetti et al. 2015; Barbieri et al. 2020).

Sensitivity to environmental changes is another important driver of sustainable practices, and location plays a crucial role in this regard. Natural phenomena such as floods, droughts and biodiversity loss affect all regions, but rural areas—where businesses are more directly tied to the environment—are often more severely impacted (Marshall et al. 2014). Rural communities tend to maintain closer interactions with their ecosystems, cultivating a local culture with greater environmental awareness than that of urban settings (Berenguer et al. 2005).

Social pressure, territorial regulations and the direct effects of environmental changes collectively contribute to greater sustainability awareness in rural areas. However, Berenguer et al. (2005) highlight a paradox: While urban residents often express stronger pro-environmental values, they tend to exhibit lower levels of environmentally responsible behaviour and intention compared with rural residents. In contrast, rural communities demonstrate more tangible environmentally compatible actions and behaviours.

The tradition of environmentally friendly practices in rural areas reflects a legacy of sustainable production methods, such as extensive livestock farming or organic agriculture. Rural businesses often possess a deeper understanding of and connection to natural processes than their urban counterparts, enabling them to adopt and lead innovative approaches to conservation, reforestation and sustainable water management. In relation to this supposedly intrinsic eco-innovation in rural areas, Iammarino (2011) highlights the potential for rural regions to integrate traditional and modern activities based on local resources. Grillitsch and Nilsson (2015) further emphasise that these innovation dynamics are driven by strong collaborative capacities among rural enterprises to secure otherwise inaccessible resources.

In terms of access to public sustainability programmes and policies, many European regions specifically target rural areas with government initiatives or subsidies designed to promote sustainable practices. These targeted efforts often complement broader initiatives aimed at all territories. Dimakopoulou et al. (2023) argue that both rural and urban businesses are motivated to pursue eco-innovation, albeit through different mechanisms. Urban firms are frequently driven by the need to reduce their ecological footprint in order to comply with environmental regulations, whereas rural firms are more strongly influenced by their direct relationship with natural resources.

Research examining the impact of firm location on environmental innovation dynamics remains relatively limited compared with other areas of study. Zhu et al. (2023) suggest that firms located in rural areas may, in some cases, exhibit a stronger inclination towards environmental innovation, motivated by a desire to preserve their surrounding environment. Conversely, urban firms are often more concerned with regulatory compliance. Regarding the influence of environmental regulation on eco-innovation and its interplay with firm location, Wang et al. (2021) caution against overly stringent environmental regulations, noting that excessive restrictions—depending on the type of territory—may prompt firms to relocate to less regulated areas. They also underline the mediating role of CSR in navigating these regulatory challenges.

In summary, the geographical location of a firm significantly shapes its interaction with and perception of the environment. For rural firms, proximity to natural resources, together with social pressures and location-specific regulations, fosters a distinct environmental awareness and motivation for sustainability. According to institutional theory (North 1990), formal and informal institutions embedded in specific locations influence organizational behaviour, including sustainability practices. These factors collectively influence their propensity to drive environmental innovation.

Based on these considerations, we propose the following hypothesis:

H1. *The geographical location of a firm (rural or urban) significantly influences its propensity for environmental innovation.*

2.2 | Business Environment and Environmental Innovation

The business environment plays a pivotal role in determining the trajectory and pace of environmental innovation. It encompasses a diverse array of factors, including (1) government policies and regulations, (2) consumer preferences and market demand, (3) economic conditions, (4) technological advancements, (5) competitive dynamics, and (6) cultural and social influences. This understanding aligns with institutional theory, which emphasises how organisational behaviour is shaped by external regulatory, normative and cultural pressures (Scott 1995).

Government policies and regulations are among the most significant drivers of environmental innovation. Stricter environmental regulations often compel firms to develop and adopt more sustainable operating methods. Simultaneously, tax incentives, subsidies and research and development (R&D) funding provided by governments serve as financial motivators, fostering the creation of green initiatives and the advancement of innovative technologies (Pérez-De-Lema et al. 2019). According to Porter and van der Linde's (1995) theory, well-designed regulations not only constrain but also stimulate firms to innovate, a perspective supported by subsequent empirical evidence (Jaffe and Palmer 1997; Horbach and Rammer 2018). However, the effectiveness of these policies can vary significantly depending on regional and institutional contexts. For example, recent studies in Asian countries highlight how ownership diversity and board composition, including gender diversity, moderate the impact of environmental, social and governance (ESG) policies on corporate environmental performance (Saleh and Maigoshi 2024). Likewise, foreign ownership and audit committee activities in financial and environmental management have been identified as key factors affecting the quality of environmental innovation in these contexts (Saleh and Mansour 2024). These findings are consistent with contingency theory, which suggests that the effect of environmental pressures depends on organisational characteristics and contextual factors (Donaldson 2001).

Consumer preferences and market demand are also critical determinants. With growing awareness of environmental issues, consumers increasingly favour eco-friendly products and services, often willing to pay a premium for sustainability. This shift creates lucrative opportunities for firms to develop innovative, environmentally conscious solutions (Ottman 2017). Resource-based and stakeholder theories complement this view by emphasising that firms can leverage market and stakeholder demands to develop unique capabilities and achieve competitive advantage (Barney 1991; Freeman 2010).

Economic conditions influence a firm's capacity for environmental innovation. A robust economy enhances access to resources and financial markets, enabling companies to invest in R&D and undertake long-term innovation projects (Hall and Lerner 2009). Technological advancements further support this process by enabling the development of more sustainable products and processes. Strong intellectual property rights incentivise innovation by ensuring firms can reap the benefits of their discoveries and safeguard their competitive edge (Hall and Harhoff 2012).

In competitive markets, intense rivalry often drives firms to innovate to gain advantage. Collaboration and partnerships with competitors and other stakeholders can facilitate the development of novel solutions (Gnyawali and Park 2011). Cultural and social factors also influence the acceptance and adoption of new technologies by encouraging engagement with stakeholders such as employees, customers and communities, thus helping firms identify and address environmental challenges (Berrone et al. 2013).

Several studies have analysed the impact of the business environment on environmental innovation, considering regulations, institutional pressures and market dynamics. Porter and van der Linde (1995) argued that well-designed environmental regulations stimulate innovation by compelling firms to develop cleaner, more efficient technologies. This view, once debated, has gained substantial empirical support. For instance, Jaffe and Palmer (1997) showed that stricter environmental regulations lead to increased innovation in pollution control technologies, evidenced by a rise in patent applications. Similarly, Horbach and Rammer (2018) found that regulatory pressures, alongside firm size, market demand and cooperation, are key determinants of environmental innovation.

Beyond regulations, institutional and market pressures also play significant roles. Berrone et al. (2013) concluded that public awareness and environmental regulations incentivise firms—particularly those with higher pollution levels—to adopt sustainable innovations. Kemp and Pearson (2007) developed a framework to measure eco-innovation's economic and environmental impact. Institutional theory (Scott 2008) provides a lens to understand how regulatory, normative and cultural-cognitive pressures shape firm behaviour toward environmental innovation.

Environmental innovation has also been examined in the context of economic crises. During the 2008 financial crisis, Kim (2015) found that firms exhibiting sustainable behaviours maintained positive innovation relationships despite adverse conditions. This aligns with Brem et al. (2020), who used OECD patent data to demonstrate that crisis impacts vary by sector and innovation type. Trantopoulos et al. (2024) further explored firms' adaptation of open innovation strategies during crises, highlighting the importance of organisational learning under uncertainty. Such findings resonate with dynamic capabilities theory, which emphasises that firms must adapt and reconfigure resources to maintain innovation under changing environments (Teece 2007).

In emerging economies and developing countries, ownership structure and CEO power significantly moderate the relationship between business environment and environmental innovation. Notably, evidence from Asian firms shows that gender diversity on boards and female CEOs can amplify the effectiveness of ESG policies in driving environmental innovation (Saleh et al. 2025; Mansour et al. 2024). Similarly, Asiaei et al. (2023) demonstrated that green intellectual capital and a favourable business environment strongly impact green innovation performance in emerging markets. Han et al. (2023) also showed that optimising the business environment enhances innovation efficiency in Chinese firms.

Finally, the role of environmental policies within the business cycle is widely recognised. Popp (2020), analysing patent and macroeconomic data, emphasised the necessity for environmental policies that foster clean technology development, which is vital for addressing climate change and sustainability challenges.

An enabling business environment—characterised by access to resources, financing and supportive regulations—thus plays a crucial role in fostering sustainability-oriented innovation. Based on this understanding, the following hypothesis is proposed:

H2. *A favourable business environment positively influences environmental innovation.*

2.3 | Digital Maturity and Environmental Innovation

Several authors have indicated that digital maturity exerts a positive influence on environmental innovation, a relationship increasingly supported by empirical and theoretical evidence (Cheng et al. 2023; Feng et al. 2022; Gollhardt et al. 2020; Liu et al. 2024; Ochoa-Urrego and Peña-Reyes 2021). This aligns with the resource-based view, which suggests that firms with superior internal capabilities—such as advanced digital infrastructures—can achieve competitive advantages and drive innovation (Barney 1991). Digital maturity fosters environmental innovation primarily by enabling enhanced access to data and advanced analytics. Digitally mature companies are better equipped to collect, store and analyse large volumes of data, allowing them to identify consumption patterns, environmental impacts and opportunities for optimisation, which ultimately lead to more effective and targeted sustainable solutions (Beier et al. 2017; Feroz et al. 2021; Ranghino 2019). In this context, the dynamic capability theory also supports the idea that firms with digital maturity can integrate, build and reconfigure internal and external competencies to address rapidly changing environments, including environmental challenges (Teece 2007).

The digital transformation introduces technologies such as the Internet of Things (IoT), artificial intelligence (AI) and blockchain, which can be applied to monitor emissions, optimise processes, track supply chains and develop more sustainable products and services (Mateo et al. 2022; Rath et al. 2024). Furthermore, digital maturity fosters a culture of agility and collaboration, enabling firms to respond rapidly to market changes, environmental regulations and evolving demands, while facilitating partnerships with other organisations to co-create innovative solutions (Nambisan 2017; Westerman et al. 2014). Stakeholder theory complements this view, suggesting that active engagement and collaboration with external partners and internal actors can enhance a firm's innovative capacity (Freeman 2010).

Digital tools are also leveraged to raise awareness of environmental issues among employees, customers and other stakeholders, thereby fostering interest and promoting the adoption of more sustainable practices (Berger et al. 2023). Through sensors and real-time analytics, digital maturity enables process optimisation by monitoring energy and water consumption, identifying reduction opportunities and implementing corrective actions (Xu et al. 2024). Technologies such as blockchain enhance transparency by tracing the origin of raw materials and products, ensuring ethical and sustainable practices throughout the supply chain (Cruz and da Cruz 2020).

Moreover, digitalisation supports the development of products and services with reduced environmental impact, including electric vehicles, biodegradable packaging and sharing economy platforms. These strategies actively engage stakeholders, as companies use social media and other digital communication tools to educate and involve them in sustainability initiatives, thereby strengthening corporate reputation and building trust (Nayal et al. 2022; Pigola et al. 2021). This reinforces the stakeholder theory principle that sustainable innovation benefits from aligning organisational practices with stakeholder expectations (Freeman 2010).

While digital maturity alone does not guarantee environmental innovation, it provides essential tools and capabilities, which, when combined with strategic vision and a commitment to sustainability, act as powerful catalysts for innovation. Companies investing in digital transformation and leveraging it to drive sustainable solutions are better positioned to tackle environmental challenges and foster a greener, more prosperous future (Jardak and Ben Hamad 2022; Mikalef et al. 2020; Venkatesan 2020). Such integration of digital capabilities and strategic orientation exemplifies the dynamic capability perspective, highlighting how firms reconfigure resources to achieve sustainability-oriented innovation (Teece 2007). Evidence from Asian contexts further supports this relationship. Recent studies suggest that digitally mature firms in Asia, particularly those led by female CEOs or with diverse boards, tend to exhibit higher levels of green innovation due to enhanced strategic decision-making and stakeholder engagement (Mansour et al. 2024; Saleh et al. 2025).

Thus, a high level of digital maturity enables organisations to harness advanced technologies and data-driven strategies that are vital to enhancing sustainable practices and driving innovation. Based on this understanding, we formulate the following hypothesis:

H3. *Digital maturity has a positive impact on environmental innovation.*

2.4 | Firm Size and Environmental Innovation

The size of a company plays a crucial role in mediating its ability to adopt environmental innovations. Depending on their size, companies exhibit distinct characteristics that can be summarised through the following factors: (1) financial and human resources, (2) economies of scale, (3) innovation capacity, (4) regulatory and stakeholder pressure, and (5) corporate culture. This perspective aligns with the resource-based view, which posits that firms with greater internal resources and capabilities—such as financial and human capital—are better positioned to implement innovative practices (Barney 1991).

Large companies typically possess greater resources for research and development (R&D) of sustainable technologies compared with smaller companies, which enhances their ability to invest in long-term projects related to environmental innovation (Wang et al. 2021). Economies of scale provide an additional advantage, enabling large firms to reduce costs by implementing sustainable technologies on a broader scale.

Regarding regulatory and stakeholder pressures, the higher economic capacity of large companies allows them to absorb costs associated with environmental compliance more easily. In contrast, smaller companies generally face less regulatory pressure, which may reduce their motivation for eco-innovation (Dimakopoulou et al. 2023). Multinational companies, in particular, are subject to heightened public and regulatory scrutiny, which encourages them to adopt CSR practices more rigorously, thereby driving environmental innovation and fulfilling stakeholder expectations (Wang et al. 2021). Stakeholder theory supports this view, emphasising that firms facing greater external pressures and expectations are more likely to innovate in ways that address both environmental and social concerns (Freeman 2010).

Corporate culture also influences the adoption of sustainability practices. While large firms typically have more structured approaches to R&D, smaller firms—despite fewer resources—tend to be more flexible and quicker in implementing changes and adopting sustainability-oriented practices (Zhu et al. 2023).

Large firms, whether located in rural or urban areas, generally have more resources to devote to R&D than smaller firms. Companies in urban areas may face stricter environmental regulations; yet larger firms are more capable of overcoming these barriers due to their resource availability. Conversely, small firms in rural areas may benefit from more lenient regulations but often lack sufficient resources to adopt innovative technologies effectively (Wang et al. 2021; Dimakopoulou et al. 2023).

Firm size also emerges as a key mediating factor in the relationship between digital maturity and environmental innovation, particularly concerning financial capacity. Larger companies generally have greater financial ability to leverage digital technologies for sustainable practices—whether through access to digital tools (e.g., AI, IoT, big data, real-time monitoring) or the implementation of digital solutions for environmental innovation. However, smaller firms' inherent flexibility allows them to adopt and adapt new technologies more rapidly and efficiently (Yao et al. 2023; Hou et al. 2024). Here, the integration of dynamic capability and contingency theories explains why firm size interacts with digital maturity to influence environmental outcomes.

Consequently, firm size acts as a moderating factor in the relationship between environmental innovation, location (rural vs. urban), business environment and digital maturity. While larger firms often have greater access to resources facilitating innovation, other factors—such as location-based environmental regulations and the characteristics of the business environment—may exert differential effects.

Evidence from developing countries demonstrates similar patterns. Research in Asian firms indicates that larger companies with diverse boards are more likely to translate digital maturity into tangible green innovation, whereas smaller firms leverage flexibility and local knowledge to implement eco-innovations effectively (Mansour et al. 2024; Saleh et al. 2025). This underscores the convergence of resource-based, stakeholder and dynamic capability perspectives, demonstrating that both internal resources and governance structures influence the adoption of environmental innovations.

These findings suggest that firm size and governance characteristics interact with digital and environmental strategies, highlighting the importance of context-sensitive approaches to sustainability.

Based on this understanding, the following hypotheses are proposed:

H4. *Firm size moderates the relationship between business location (rural vs. urban) and environmental innovation.*

H5. *Firm size moderates the relationship between business location and environmental innovation.*

H6. *Firm size moderates the relationship between digital maturity and environmental innovation.*

Figure 1 presents the conceptual framework of the study, illustrating the relationships underlying the proposed hypotheses. Hypothesis H1 posits that firm location—specifically whether a company operates in a rural or urban environment—significantly influences its capacity for environmental innovation. Hypothesis H2 suggests that the general business environment plays a pivotal role in fostering such innovation. Hypothesis H3 emphasises the importance of digital maturity as a key determinant of a firm's capabilities to develop environmentally innovative solutions. The framework further incorporates firm size through three moderating hypotheses: H4 proposes that firm size moderates the relationship between firm location and environmental innovation; H5 suggests that firm size influences the connection between the business environment and environmental innovation; H6 posits that firm size moderates the relationship between digital maturity and environmental innovation. Collectively, the framework highlights the complex, multifaceted interactions among location, business environment, digital maturity and firm size in shaping sustainability-oriented innovation.

3 | Research Methodology

3.1 | Description of the Data

To predict environmental innovation using ML techniques, this study utilised micro-data from the 2020 Flash Eurobarometer 486 survey, conducted by the European Commission. The survey focused on “SMEs, start-ups, scale-ups and entrepreneurship” and provides a comprehensive dataset capturing the challenges and opportunities faced by businesses across Europe. It emphasises their innovation trajectories, the adoption of environmentally sustainable practices and the integration of digital technologies into their operations (European Commission 2020). The 486th Eurobarometer survey includes data from all 27 EU Member States and 12 additional countries, offering a broad perspective on diverse business environments and economic conditions. The dataset is recognised for its accuracy and reliability, as it follows strict validation protocols established over years of research.

Data were gathered through extensive telephone interviews with senior managers or key decision-makers from 16,365 companies with at least one employee, between 19 February and 5 May 2020. The sampling frame excluded self-employed individuals without employees. Companies were selected using random stratified sampling, ensuring representativeness by country, firm size and sector. The survey design also included interviewer training and validation checks to minimise bias and ensure consistency in responses. After excluding firms with

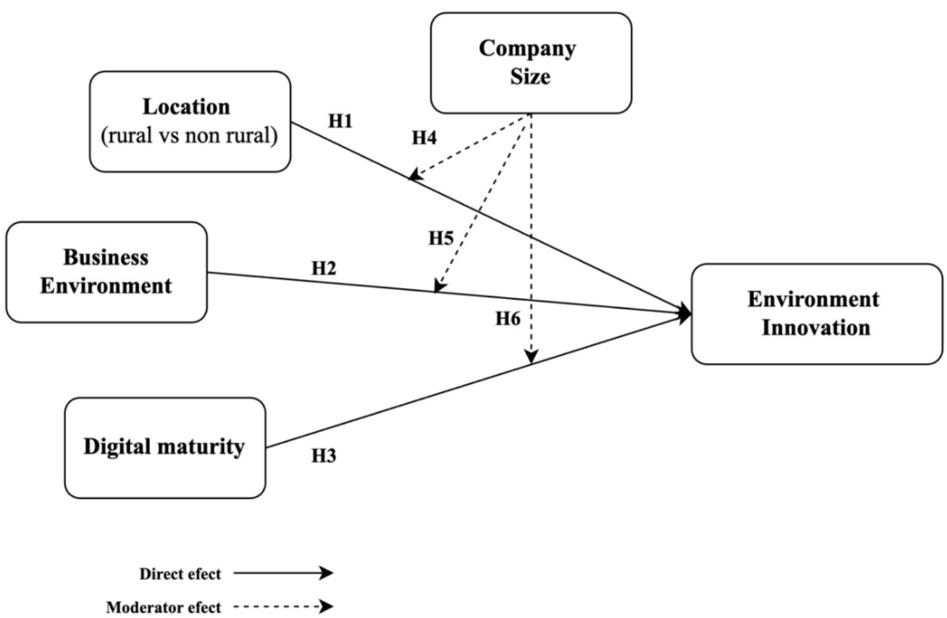

FIGURE 1 | Theoretical framework.

missing information in core variables (location, business environment, digital maturity, environmental innovation), the final analytical sample included 15,976 firms. This carefully designed sampling procedure provides a robust and representative dataset, enabling reproducible empirical studies on the determinants of environmental innovation across nations.

3.2 | Measures

3.2.1 | Dependent Variables

3.2.1.1 | Environmental Innovation. To measure environmental innovation, we use the following variable: "During the past 12 months, has your company introduced an innovation with an environmental benefit, including innovations that promote energy efficiency or resource efficiency?" This variable is categorised as binary, enabling the identification of whether companies have implemented sustainable innovations in their operations.

3.2.2 | Independent Variables

3.2.2.1 | Location. For the rural variable, a binary classification was employed to categorise enterprises according to their geographical context, specifically distinguishing those situated in rural areas. This approach facilitates a clear analysis of how location influences environmental innovation and the role geography plays in shaping innovation outcomes.

3.2.2.2 | Business Environment. For the assessment of the business environment, several survey items were utilised, encompassing the overall strength and performance of the regional business environment, as well as specific factors such as access to private and public finance; the quality of support services provided by both private and public entities; access to and collaboration with business partners (including other firms, the public sector, educational institutions and research organisations); the availability of staff possessing the necessary competencies (including management skills); support for businesses aiming to become more sustainable; the legal and administrative environment; infrastructure for businesses (such as office space and internet connectivity). Respondents rated these items on a scale from "very bad" (1) to "very good" (4). Following the extraction of the principal component, the data were normalised to values between 0 and 1 using the formula:

$$x' = \frac{x - \min}{\text{range}}$$

3.2.2.3 | Digital Maturity. To assess the digital maturity of the company, we utilised a specific question from the survey: "Has your company implemented any of the following digital technologies?" Respondents answered with a simple "yes" or "no" for each option, which included a range of digital technologies such as AI, cloud computing, robotics, smart devices, big data analytics, high-speed digital infrastructure and blockchain technology. Based on the number of technologies implemented, we constructed a cumulative index aggregating these seven categories. This index was then normalised to values between 0 and 1 to facilitate comparison and analysis.

3.2.3 | Moderating Variable

3.2.3.1 | Company Size. To assess firm size, we focused on the number of employees, excluding owners, as this metric provides a clear indicator of the organisation's scale and operational capacity. This approach enables analysis of how firm size influences various aspects of business performance, including environmental innovation.

3.2.4 | Control Variables

We incorporated several control variables to account for potential influences on environmental innovation outcomes. These included the country of operation, industry sector, the firm's duration in the market and whether the firm engages in export activities. By considering these factors, we aimed to isolate the effects of our primary independent variables on environmental innovation, ensuring a more accurate assessment of their relationships while controlling for contextual and operational differences across firms in the dataset.

3.3 | Data Analysis

This study applies a combination of statistical and ML methods to investigate the determinants of environmental innovation. The dependent variable is binary, indicating whether a firm has introduced an innovation with environmental benefits during the previous 12 months. Logistic regression and LDA serve as traditional benchmarks, allowing hypothesis testing and interpretable coefficients aligned with theory. However, their assumption of linearity restricts their ability to capture the complex and potentially nonlinear interactions among firm characteristics.

To address this limitation, we employed a range of binary classifiers, each designed to predict categorical outcomes with two classes. Decision trees generate interpretable rules by partitioning firms based on key attributes, while random forests enhance stability by averaging across multiple trees. SVMs are effective for identifying separating boundaries in high-dimensional, nonlinear data. GBs) refine predictions iteratively, capturing subtle interaction effects. Naïve Bayes provides a simple, probabilistic baseline, and KNN uses similarity measures to classify firms. Finally, ANNs detect complex nonlinear patterns that are difficult to capture with conventional methods.

By combining interpretable and predictive approaches, the study ensures both theoretical transparency and analytical depth. To safeguard against overfitting, the dataset was divided into a training set (70%) and a testing set (30%), enabling out-of-sample validation and ensuring the generalisability of results.

The selection of algorithms was guided by their suitability for binary classification tasks and their complementary strengths, ranging from interpretable models (logistic regression, LDA) to more flexible non-linear classifiers (RF, GB, SVM, ANN), allowing a balanced assessment of predictive performance.

This methodological approach goes beyond traditional techniques by combining interpretable models with advanced ML classifiers and partial dependence plots (PDPs), thereby capturing complex nonlinearities and providing a more robust understanding of environmental innovation drivers.

3.4 | Evaluation Metrics

Evaluating the performance of classification models is essential to ensure accurate predictions and to assess the effectiveness of the model for a given task. Several performance metrics—such as accuracy, precision, recall, F1-score and AUC (area under the ROC curve)—offer insights into various aspects of model performance, including accuracy, robustness and generalisability. The choice of metric depends on the characteristics of the data and the objectives of the classification task.

Precision is commonly used but is most effective with balanced datasets, as it may be misleading when applied to imbalanced data. Precision and recall are particularly useful when the objective is to minimise false positives and false negatives, respectively. The F1-score provides a balanced measure between precision and recall, making it valuable when a trade-off exists between the two. The ROC curve and AUC deliver a more comprehensive evaluation of model performance across different decision thresholds, making them especially advantageous for imbalanced classification problems.

4 | Results

4.1 | Description of Data

Table A1 presents summary statistics for the variables in the dataset, including the minimum, maximum, median, mean and standard deviation (SD) for each variable. Export activity was reported by 34.1% of firms, indicating that over one-third were involved in international trade, which is often associated with more dynamic business strategies and potentially greater innovation-driven practices.

Regarding firm size, the average number of employees (excluding owners) was 143, with a substantial range from 0 to over 9900 employees. This highlights considerable variation in firm size, suggesting that the sample included both very small firms (some with no employees beyond the owners) and much larger companies with extensive workforces.

Rural location applied to 10.3% of firms, implying that the majority were situated in non-rural areas, likely benefiting from proximity to infrastructure and more developed markets. This urban–rural divide may further influence access to resources, innovation networks and technology adoption.

The digital maturity variable, reported at 20.5%, reflects relatively low levels of technology adoption across the surveyed companies. This suggests that many firms were at varying stages of digital transformation, with some still lagging behind in integrating advanced digital tools and platforms into their operations.

The business environment score stood at 35%, reflecting companies' perceptions of their operating climate, including factors such as regulatory support, market access and economic stability. This score helps contextualise the challenges or advantages firms faced depending on their country and sector.

The distribution of companies across countries was generally homogeneous, with most countries represented by approximately 3% of the sample. This even distribution, observed in countries such as France, Germany and Austria, ensured that no single country dominated the dataset, allowing for balanced comparisons. Notable exceptions included smaller countries like Luxembourg (1.2%) and Kosovo (1.3%), which were less represented; however, this variation is expected given the relative size and economic activity of these nations.

Sector-wise, the data reveal diverse industry representation. Manufacturing accounted for 19.5% of firms, indicating a strong presence of production activities often linked to innovation and environmental sustainability practices. The wholesale and retail trade sector comprised 27.7%, reflecting its economic importance and potential role in supply chain innovations. Other sectors, such as construction (9.7%), professional and scientific activities (9.4%) and administrative services (4.4%), also contribute to the dataset's industrial variety. Mining and quarrying (0.6%) and the electricity, gas, steam and air conditioning sector (0.6%) were minimally represented, likely due to their more specialised economic roles.

This balanced distribution across sectors and countries ensures a robust dataset that supports generalisable conclusions and meaningful comparisons across regions and industries when examining environmental innovation, digital maturity and other factors. The even country representation further strengthens the analysis by preventing any single region from skewing the results, providing clearer insights into how various contextual factors influence business practices and innovation performance.

4.2 | Performance of the Models

Table 1 presents a detailed comparison of the performance of various ML algorithms applied to predict whether a company had implemented an innovation with environmental benefits, such as those that improve energy or resource efficiency. The performance metrics analysed include accuracy, precision, recall, F1-score and AUC, providing a comprehensive assessment of each model's predictive capabilities.

Overall, the models show heterogeneous performance. Logistic regression, LDA and GB emerged as the most balanced, combining solid accuracy (≈0.78) with AUC values above 0.71, making them reliable for distinguishing adopters from non-adopters. Decision trees and KNN performed less effectively, either due to overfitting or sensitivity to data structure. SVM and ANN achieved very high recall, identifying nearly all positive cases,

TABLE 1 | Performance comparison of machine learning algorithms.

Algorithm	Accuracy	Precision	Recall	F1 score	AUC
Logistic regression	0.7847	0.7916	0.9809	0.6077	0.7160
Linear discriminant analysis	0.7803	0.8005	0.9551	0.5256	0.7178
Decision tree	0.7765	0.7765	1.0000	NaN	0.6270
Random forest	0.7667	0.8042	0.9248	0.4542	0.6845
Support VM	0.7768	0.7768	0.9997	0.6667	0.6590
Gradient boosting	0.7843	0.7902	0.9833	0.6149	0.7186
Naive Bayes	0.7580	0.8013	0.9154	0.4177	0.6830
K-nearest neighbours	0.6555	0.6899	0.8906	0.7768	0.5753
Neural networks	0.7805	0.7818	0.9952	0.6727	0.6734

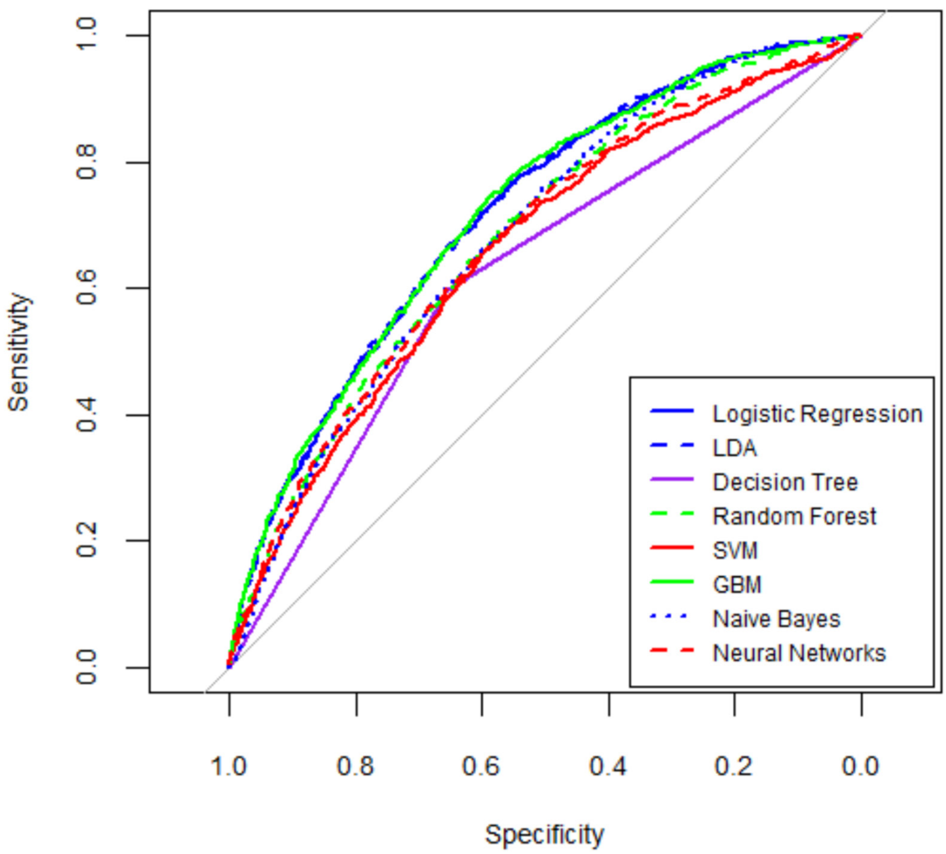

FIGURE 2 | ROC curves for different machine learning algorithms.

but at the expense of lower precision and moderate AUC, indicating reduced balance. Random forest and Naive Bayes delivered intermediate results, confirming their utility but not outperforming the stronger models. These differences underline the importance of comparing algorithms, as each highlights distinct trade-offs between interpretability, sensitivity and predictive robustness.

Models such as GBM and logistic regression achieved stronger predictive balance, combining recall and precision effectively, while KNN and ANN performed less consistently. The weaker results of KNN reflect its sensitivity to data structure and class imbalance, while ANN performance was limited by sample heterogeneity and the risk of overfitting with relatively shallow architectures. These differences underline the importance of comparing diverse classifiers rather than relying on a single technique.

Figure 2 presents the ROC curves for the ML models employed in this study, illustrating their ability to distinguish between companies that have implemented environmental innovations and those that have not. The ROC curves visually depict the trade-off between the true positive rate (sensitivity) and the false positive rate, while the AUC scores provide a quantitative measure of each model's overall performance. Models such as logistic regression, LDA and GB demonstrate higher AUC values, indicating strong classification capabilities, whereas models such as decision trees and KNN exhibit weaker performance, as reflected by their lower AUC scores and reduced effectiveness in class differentiation.

4.3 | Logistic Regression and LDA

Table 2 presents the logistic regression results, including odds ratios (OR), 95% confidence intervals (95% CI) and *p*-values, alongside the canonical discriminant function derived from LDA. These results are essential for evaluating the proposed hypotheses and understanding the factors influencing firms' adoption of environmental innovations. Logistic regression provides a detailed analysis of the relative likelihoods associated with each variable, while LDA assists in distinguishing between firms that have adopted environmental innovations and those that have not.

The logistic regression and LDA results provide direct evidence for the proposed hypotheses. H1 is supported, as firms located in rural areas are significantly more likely to adopt environmental innovations (OR = 1.40, 95% CI: 1.20–1.64, $p < 0.01$), a finding reinforced by the positive LDA coefficient (0.424). H2 is also supported, with a favourable business environment nearly tripling the odds of adoption (OR = 2.98, 95% CI: 2.11–4.20, $p < 0.01$) and LDA showing the strongest positive coefficient (3.411). H3 receives strong support, as digital maturity emerges as the most influential factor, increasing the likelihood of environmental innovation almost thirteenfold (OR = 12.96, 95% CI: 10.04–16.73, $p < 0.01$), consistent with the positive LDA coefficient (1.154). By contrast, H4 is not supported, since the interaction between firm size and rural location is not significant in logistic regression (OR = 0.98, $p = 0.841$) and shows no effect in LDA (0.000). H5 receives partial support, as logistic regression indicates a significant positive interaction between firm size and business environment (OR = 1.04, 95% CI: 1.00–1.07, $p < 0.05$), although LDA does not confirm this result. Finally, H6 is not supported, with no significant interaction between firm size and digital maturity (OR = 0.99, $p = 0.154$) and a negligible negative coefficient in LDA (−0.001). In summary, H1–H3 are fully supported, H4 and H6 are not supported, while H5 shows limited evidence of support.

Beyond the main hypotheses, several firm-level and contextual factors emerged as significant. The length of time a firm has been in operation exerts a positive effect, with each additional year increasing the probability of adoption by 2% (OR = 1.02, $p < 0.01$). Exporting firms are also more likely to innovate environmentally (OR = 1.32, $p < 0.01$), reflecting the influence of international market pressures and regulatory frameworks. Firm size itself shows a positive association (OR = 1.02, $p < 0.01$), confirming that larger firms have a greater propensity to adopt eco-innovations.

Industry effects further differentiate innovation patterns. No sector demonstrates higher odds of adoption than mining and quarrying (reference), but several sectors exhibit significantly lower adoption rates, including information and communication (OR = 0.24, $p < 0.01$), professional and scientific activities (OR = 0.38, $p < 0.01$), construction (OR = 0.51, $p < 0.05$), wholesale and retail trade (OR = 0.52, $p < 0.05$) and financial and insurance activities (OR = 0.45, $p < 0.05$). These results suggest that eco-innovation is unevenly distributed across industries, with knowledge-intensive and service-based sectors lagging behind.

The LDA results broadly confirm these findings, with positive coefficients for exporters (0.328) and older firms (0.006), as well as negative coefficients for countries and industries with lower adoption propensities. Together, logistic regression and LDA highlight the role of firm-specific characteristics, internationalisation, territorial context and sectoral affiliation in shaping the likelihood of environmental innovation, complementing the hypothesis-driven results on location, business environment and digital maturity.

4.4 | Gradient Boost Machines

Using GB, we assess the relative importance of various firm characteristics and interaction effects to better understand the key drivers of environmental innovation adoption. The first step involves evaluating the importance of each variable, which enables us to determine their respective contributions to the model's predictive accuracy. This approach facilitates the identification of the most influential factors driving environmental innovation. Furthermore, PDPs are employed to explore interaction effects between firm size and critical variables—namely, rural location, business environment and digital maturity. This analysis clarifies how firm size influences the capacity to adopt sustainable practices, particularly when operating in rural settings, within favourable business environments, or with high digital maturity.

The factor importance analysis, presented in Table 3 shows the relative importance of different factors in explaining environmental innovation. Among the core variables, H1 receives only weak support, as rural location shows a very modest contribution (1.03%), suggesting that geography matters but less than other factors. H2 is supported, with the business environment accounting for 4.57% of predictive power, confirming its role as an enabling condition. H3 is strongly supported, since digital maturity emerges as the most relevant firm-level driver (27.48%), substantially increasing the likelihood of adoption.

Beyond the hypotheses, several contextual variables are decisive. The country of operation is the single most influential factor (43.25%), underlining the importance of national institutions and regulatory frameworks. Industry sector (12.84%) and firm size (7.09%) also shape adoption probabilities, while export activity (1.29%) and firm age (2.45%) exert smaller but non-negligible effects.

In addition, we utilise PDPs as effective visualisation tools to examine the marginal effects of two variables on the predicted likelihood of adopting environmental innovations. The PDP analysis reveals how variations in selected factors impact the

TABLE 2 | Logistic regression and linear discriminant analysis results.

Variables	O (CI 95%)	P	CDFC
(Intercept)	0.41 (0.21–0.80)	0.007	
BE—Belgium	1.14 (0.79–1.64)	0.478	0.197
NL—The Netherlands	0.87 (0.60–1.26)	0.456	−0.128
DE—Germany	1.25 (0.87–1.80)	0.209	0.309
IT—Italy	0.42 (0.26–0.66)	0.000**	−0.760
LU—Luxembourg	1.19 (0.75–1.89)	0.456	0.281
DK—Denmark	1.57 (1.09–2.24)	0.012*	0.663
IE—Ireland	0.87 (0.60–1.27)	0.471	−0.103
GB—United Kingdom	0.98 (0.68–1.42)	0.922	0.002
GR—Greece	0.34 (0.22–0.52)	0.000**	−1.070
ES—Spain	1.13 (0.79–1.62)	0.496	0.238
PT—Portugal	1.24 (0.86–1.79)	0.230	0.371
FI—Finland	0.85 (0.58–1.23)	0.368	−0.148
SE—Sweden	0.96 (0.67–1.37)	0.813	−0.009
AT—Austria	0.96 (0.67–1.39)	0.841	−0.006
CY—Cyprus (Republic)	0.34 (0.19–0.61)	0.000**	−1.106
CZ—Czech Republic	1.19 (0.83–1.71)	0.337	0.231
EE—Estonia	0.48 (0.31–0.73)	0.000**	−0.742
HU—Hungary	0.63 (0.42–0.95)	0.026*	−0.483
LV—Latvia	1.19 (0.83–1.71)	0.339	0.256
LT—Lithuania	0.15 (0.08–0.28)	0.000**	−1.184
MT—Malta	0.81 (0.49–1.33)	0.388	−0.229
PL—Poland	1.35 (0.94–1.95)	0.100	0.426
SK—Slovakia	0.83 (0.56–1.23)	0.340	−0.191
SI—Slovenia	0.54 (0.36–0.80)	0.002**	−0.689
BG—Bulgaria	1.05 (0.72–1.54)	0.787	0.094
RO—Romania	0.47 (0.30–0.72)	0.000**	−0.710
TR—Turkey	0.82 (0.53–1.25)	0.338	−0.198
HR—Croatia	0.29 (0.19–0.47)	0.000**	−1.101
MK—North Makedonia	0.47 (0.26–0.83)	0.008**	−0.733
RS—Serbia	0.37 (0.19–0.70)	0.002**	−0.835
NO—Norway	0.86 (0.56–1.31)	0.478	−0.171
IS—Iceland	1.60 (1.01–2.55)	0.045*	0.704
JP—Japan	0.68 (0.41–1.11)	0.114	−0.411
US—USA	0.33 (0.22–0.51)	0.000*	−1.170
BR—Brazil	0.92 (0.61–1.38)	0.680	−0.039
BA—Bosnia and Herzegovina	0.13 (0.05–0.34)	0.000*	−1.335
RS-KM—Kosovo	0.67 (0.39–1.15)	0.138	−0.438

(Continues)

TABLE 2 | (Continued)

Variables	O (CI 95%)	P	CDFC
CA—Canada	0.57 (0.39–0.85)	0.005**	−0.633
C—Manufacturing	0.60 (0.33–1.09)	0.086	−0.581
D—Electricity, gas, steam and air conditioning supply	1.48 (0.67–3.29)	0.326	0.681
E—Water supply, sewerage, waste management/remediation activities	1.00 (0.49–2.07)	0.995	0.044
F—Construction	0.51 (0.28–0.93)	0.026*	−0.789
G—Wholesale and retail trade, repair of motor vehicles and	0.52 (0.29–0.94)	0.028*	−0.754
H—Transportation and storage	0.68 (0.37–1.25)	0.205	−0.473
I—Accommodation and food service activities	0.83 (0.45–1.55)	0.557	−0.217
J—Information and communication	0.24 (0.13–0.47)	0.000**	−1.617
K—Financial and insurance activities	0.45 (0.23–0.87)	0.016*	−0.954
L—Real estate activities	0.65 (0.34–1.26)	0.198	−0.477
M—Professional, scientific and technical activities	0.38 (0.20–0.69)	0.001**	−1.114
N—Administrative and support service activities	0.39 (0.21–0.74)	0.003**	−1.074
P—Education	0.71 (0.37–1.37)	0.294	−0.365
Q—Human health and social work activities	0.41 (0.22–0.79)	0.006*	−1.050
R—Arts, entertainment and recreation	0.60 (0.30–1.20)	0.139	−0.607
Time of activity	1.02 (1.01–1.04)	0.000**	0.006
Exporting activity	1.32 (1.18–1.48)	0.000**	0.328
Size	1.02 (1.02–1.02)	0.002**	0.000
Rural (H1)	1.40 (1.20–1.64)	0.000**	0.424
Bus_environment (H2)	2.98 (2.11–4.20)	0.000**	3.411
Digital_maturity (H3)	12.96 (10.04–16.73)	0.000**	1.154
Size:rural (H4)	0.98 (0.96–1.00)	0.841	0.000
Size:bus_environment (H5)	1.04 (1.00–1.07)	0.041*	0.000
Size:digital_maturity (H6)	0.99 (0.97–1.01)	0.154	−0.001

Abbreviations: CDFC, canonical discriminant function coefficients; CI, confidence intervals; OR, odds ratio.
*$p<0.05$.
**$p<0.01$.

predicted adoption probability while holding all other variables constant. These plots also illustrate the interaction effects of firm size on the relationships between business environment, digital maturity and environmental innovation adoption (Figure 3).

The plot on the left depicts the interaction between firm size and business environment.

Results show that H5 is supported, as larger firms benefit more from favourable business environments, with adoption probabilities rising faster than in smaller firms. It shows that, as the business environment improves, the likelihood of adopting environmental innovations increases across firms of all sizes. This effect is stronger for larger firms, indicating that a favourable business environment has a greater positive influence on innovation adoption when firm size is larger. This finding supports hypothesis H5, which posits that firm size moderates the relationship between business environment and environmental innovation adoption.

A similar pattern emerges in the right-hand plot of Figure 3, which depicts the interaction between firm size and digital maturity. H6 receives partial support, as the positive effect of digital maturity on environmental innovation is more pronounced in larger firms, while smaller firms show only modest gains.

In summary, both PDP analyses reveal a clear moderating influence of firm size on the effects of business environment and digital maturity in driving the adoption of environmental innovations.

5 | Discussion

This study aims to investigate the relationships between business location, business environment, digital maturity and environmental innovation, with particular attention to how firm size moderates these interactions. Specifically, the objectives include examining the influence of location (rural vs. urban) on environmental innovation (H1), assessing the impact of the business environment on eco-innovation dynamics (H2) and understanding the role of digital maturity in fostering environmentally sustainable practices (H3). Additionally, the study explores whether firm size moderates these relationships (H4, H5 and H6).

TABLE 3 | Relative importance of variables

	Importancia relativa
Country	43.25
Digital maturity	27.48
Sector	12.84
Size	7.09
Business environment	4.57
Year	2.45
Exporting activity	1.29
Rural location	1.03
Size:rural	0.00
Size:digital_maturity	0.00
Size:bus_environment	0.00

The results confirm that firm location significantly affects environmental innovation (H1), supporting the notion that firms in rural areas are more inclined to adopt sustainable practices compared with their urban counterparts. This underscores the importance of geographical context in shaping firms' innovation capabilities. Rural firms may face unique sustainability challenges that prompt innovation. This finding aligns with Battisti and Perry (2011), who argue that rural firms, being in closer contact with natural resources, develop a stronger sense of environmental responsibility, fostering a culture of sustainability distinct from urban firms (Berenguer et al. 2005). Our findings extend this perspective, indicating that the factors driving environmental innovation in rural areas are more significant than those identified by Ghisetti et al. (2015) and Barbieri et al. (2020), who emphasise industrial agglomeration in urban settings as a driver of innovation.

Furthermore, the analysis reveals that a positive business environment increases the likelihood of environmental innovation (H2). This finding is consistent with existing literature highlighting the role of external factors, such as supportive regulations, favourable market conditions and growing consumer demand, in promoting sustainable innovation. For instance, stricter environmental regulations create incentives for firms to adopt cleaner technologies (Porter and van der Linde 1995), while market demand for sustainable products motivates firms to embrace greener practices (Ottman 2017). Consumer preferences increasingly favour environmentally friendly solutions, further driving firms toward sustainability. The ability of firms to leverage these external conditions is essential for successful innovation, as evidenced by studies linking favourable business environments to higher innovation adoption rates (Jaffe and Palmer 1997; Berrone et al. 2013).

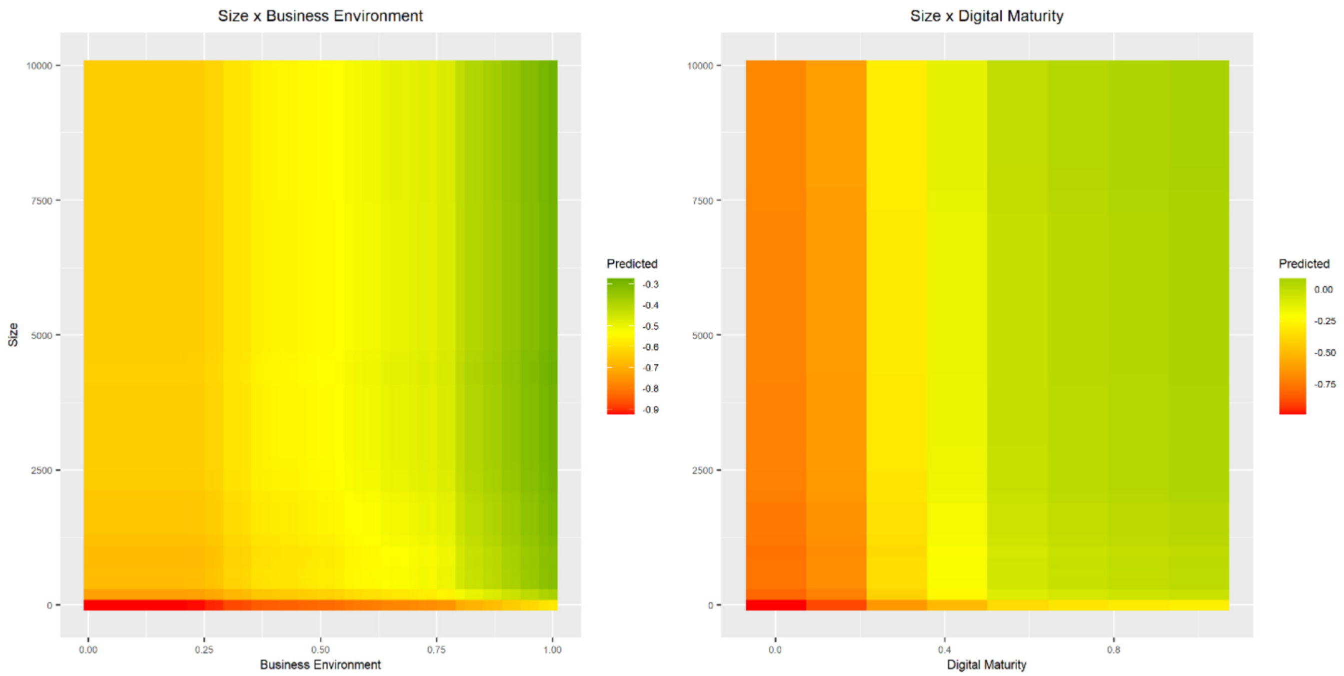

FIGURE 3 | PDPs for the interaction of size with the business environment and digital maturity

Digital maturity also emerges as a significant driver of environmental innovation (H3). Firms with advanced digital capabilities can utilise data and technology to implement sustainable practices more effectively. This underscores the critical role of digital transformation in enabling innovation. Prior research shows that organisations with higher digital maturity are better positioned to adopt environmentally friendly practices, as digital tools enable efficient monitoring, analysis and optimisation of processes (Chen et al. 2023; Feng et al. 2022). Technologies such as the IoT and AI enhance firms' ability to identify sustainability opportunities and improve environmental performance (Ochoa-Urrego and Peña-Reyes 2021). As investments in digital capabilities continue to grow, the potential for sustainable innovation is expected to increase, highlighting digital maturity's pivotal role.

Regarding the moderating role of firm size on the relationship between geographical location and environmental innovation (H4), our results do not show a significant effect. This suggests that the influence of rural or urban location on innovation outcomes operates independently of firm size. Both large and small firms appear similarly affected by the sustainability pressures and resources inherent to their geographic context. For example, in rural areas, proximity to natural resources and local environmental regulations may incentivise sustainable practices regardless of firm size. Reinforcing this idea, Galliano et al. (2023) show how the impact of spatial externalities (specialisation, related and unrelated variety) can compensate for size constraints in rural contexts. Similarly, Kyriakopoulos (2024) highlights how territorial antecedents in sustainable growth (local networks, social capital and territorial dynamics) drive innovation in rural businesses regardless of their size. Likewise, in urban areas, infrastructure and access to innovation networks may similarly influence firms of all sizes. This finding contrasts with studies suggesting that larger firms have an advantage due to greater resource availability (Wang et al. 2021) and may instead indicate that smaller firms' flexibility and adaptability compensate for fewer financial resources in specific geographic contexts (Zhu et al. 2023).

In contrast, firm size does moderate the relationship between business environment and environmental innovation (H5). Larger firms are better positioned to leverage a favourable business environment due to their greater resources and capabilities. This aligns with Porter and van der Linde (1995), who argue that environmental regulations incentivise innovation, particularly in larger firms capable of compliance. Dimakopoulou et al. (2023) similarly note that larger firms face stronger institutional pressures to adopt sustainable innovations from stakeholders. Our findings thus support literature emphasising that larger firms capitalise more effectively on innovation opportunities presented by supportive business environments.

As for how company size affects the impact of digital maturity on environmental innovation, it should be noted that although smaller companies often show greater flexibility in adopting new technologies (Yao et al. 2023; Hou et al. 2024), our results highlight that digital maturity enhances the likelihood of sustainable innovation more substantially in larger firms (H6). This underscores the importance of firm size in realising the benefits of digital investments for environmental innovation. Larger firms appear better equipped to harness digital maturity's full potential to drive sustainable practices, reinforcing the critical moderating role of firm size in the interplay between digital transformation and environmental innovation.

It is worth highlighting two deviations already mentioned but which are worth emphasising due to their value in interpreting the results. The first, of a theoretical nature, is the absence of a moderating effect of size on the location–eco-innovation relationship (H4), suggesting that territorial constraints operate largely independently of internal resources (Galliano et al. 2023; Kyriakopoulos 2024). The second, methodological in nature, is the contrast in H6: While logistic regression does not detect interaction, nonlinear models interpreted with PDPs do reveal clear patterns in larger companies, underlining the usefulness of methodologies capable of capturing nonlinearities and threshold effects in eco-innovation (Molnar et al. 2023).

Finally, from a methodological perspective, the comparison of algorithms underscores the value of combining traditional statistical models with advanced ML classifiers. Logistic regression and LDA provided interpretable results with consistent predictive balance, while GB captured complex, nonlinear patterns with strong accuracy and AUC. Conversely, KNN and, to some extent, ANN revealed the limits of certain methods when applied to heterogeneous survey data, being more sensitive to class imbalance and prone to overfitting. SVM delivered very high recall but at the cost of reduced balance. These contrasts highlight that no single model is universally superior; instead, the simultaneous use of complementary approaches enhances both predictive robustness and explanatory depth, thereby strengthening the methodological contribution of this study.

5.1 | Theoretical Implications

From a theoretical perspective, our results reinforce a systemic and contextual interpretation of eco-innovation. The greater propensity for innovation in rural environments invites a reevaluation of urban-centric perspectives, recognising territory as a relational device where networks of cooperation, social proximity and local governance—characteristics of territorial innovation systems and social capital theory—can mitigate scale limitations and guide sustainable trajectories adapted to the local context (Cooke 1992; Putnam 2000). At the same time, the business environment operates as an institutional-relational ecosystem that integrates norms, resources, infrastructure, collaboration and skills; its positive impact on eco-innovation is aligned with the neo-institutional approach and stakeholder theory, as the pressures and expectations of relevant actors become incentives and opportunities, amplified by open innovation dynamics (Scott 1995; Freeman 2010; Chesbrough 2003). Digital maturity, for its part, stands as a meta-capability aligned with the resource-based view and dynamic capabilities, facilitating the detection, capture and reconfiguration of processes towards sustainability, whose interaction with organisational scale points to thresholds and increasing returns when adequate capabilities and structures are present (Barney 1991; Teece 2007). This intersection also adds value or depth to legitimacy theory: Digital maturity drives environmental innovation and enables digital traceability. This fosters pragmatic, moral and cognitive legitimacy, allowing organisations to gain social acceptance in diverse territorial contexts, regardless of their size or location. This explains the drive for eco-innovation in rural and urban environments, even when the organisational scale does not alter the impact of location.

In summary, the findings support a configurational approach to eco-innovation: The territory and the institutional-relational ecosystem act as drivers and constraints, while resources and capabilities, with digital maturity as a pivotal meta-capability, determine their appropriation according to the organisational scale. This framework invites us to transcend additive approaches, instead modelling contingencies and nonlinearities and promoting a theoretical synthesis that articulates relational, institutional and legitimacy dynamics in the future agenda of eco-innovation.

Another key contribution of this research lies in the application of advanced ML techniques, which overcome the limitations inherent in traditional statistical approaches. Conventional methods often struggle to capture complex patterns and dynamic interactions between variables, limiting a comprehensive understanding of their interrelationships. By employing these innovative methods, this study offers more accurate and reliable inferences, providing deeper insights into the drivers of environmental innovation. Consequently, these findings strengthen both the validity and applicability of environmental innovation research. Going into greater detail, the available evidence suggests that the factors explaining innovation and eco-innovation in particular do not respond in a strictly linear fashion, but rather depend on thresholds, interactions and complex dynamics. In this regard, applying methodologies that capture these nonlinearities is particularly advisable. The results of this work point to the usefulness of integrating PDPs with ensemble algorithms in empirical studies on innovation, as this combination allows for more accurate identification of threshold effects and interactions between variables, such as those observed between digital maturity and company size in certain contexts (Molnar et al. 2023).

Together, these theoretical contributions enrich the existing body of literature and open the door to more integrative, context-sensitive and methodologically sophisticated conceptual models in environmental innovation research.

5.2 | Managerial Implications

This study emphasises that environmental innovation should not be seen merely as a reactive response to regulatory or market pressures, but as a strategic lever for organisational transformation, operational efficiency and the creation of shared value—aligned with the principles of the 2030 Agenda for Sustainable Development. For management teams, this entails expanding the firm's role beyond a purely economic entity to a co-responsible actor in the transition toward more sustainable, inclusive and resilient development models.

The findings indicate that eco-innovation presents a dual opportunity: It contributes meaningfully to the SDG—particularly SDG 8.4 on resource efficiency, SDG 9 on sustainable innovation and SDG 12 on responsible production—while enhancing business competitiveness through circular economy initiatives, energy consumption reduction and production process optimisation. These practices not only mitigate environmental impacts but also generate tangible cost savings, foster strategic differentiation and strengthen legitimacy among stakeholders.

Digital maturity emerges as a critical enabler of this transformation. Beyond technology adoption, the key lies in cultivating organisational capabilities that integrate data analytics, automation and sustainability-oriented decision-making. Digitisation and environmental innovation are interdependent processes whose synergy drives progress toward smarter, more sustainable production models.

Furthermore, a favourable business environment acts as a catalyst for innovation in both rural and urban contexts. Rural environments, in particular, may offer underutilised strategic assets—such as social capital, proximity to natural resources and supportive local regulatory frameworks—that organisations can leverage effectively. Leaders must mobilise collaborative networks, supportive infrastructure and institutional mechanisms to maximise their firms' innovative capacities in any context.

In summary, management teams face both the opportunity and responsibility to align strategies with global sustainability imperatives. When integrated coherently with digitalisation, operational efficiency and societal commitment, sustainability can become a systemic competitive advantage. To maximise these benefits, managers should prioritise digital skills training, foster strategic alliances, especially in rural contexts, and collaborate with local governments to design tax incentives that accelerate the adoption of sustainable technologies.

Finally, strategic decisions should be grounded in internationally recognised sustainability frameworks and assessment models. The triple bottom line (TBL) framework helps management balance and monitor economic, social and environmental dimensions, fostering organisational resilience (Rashidi et al. 2020). Implementing an environmental management system based on ISO 14001 enables measurable improvements in environmental performance (Arimura et al. 2011). ESG indicators provide robust criteria for monitoring and communicating sustainable achievements and risks at both strategic and operational levels (de Souza Barbosa et al. 2023; De Giuli et al. 2024).

Integrating sustainability assessment models with technology adoption and supply chain practices allows the design of holistic, evidence-based strategies that create value for both the company and society. Incorporating sustainability metrics throughout the supply chain—improving transparency, supplier collaboration and traceability—drives greater digital maturity and tangible sustainable performance. Anchoring management in standardised assessment models ensures consistency, credibility and comparability of progress. Operationally, this includes circular economy practices such as waste segregation at source, reverse logistics, digital product passports and recovery agreements with suppliers. These routines enhance the structural facilitation of sustainable behaviour, reduce the intention–behaviour gap (Barr 2004) and enable performance improvements to be audited through TBL/ESG frameworks and ISO 14001.

5.3 | Methodological Contribution

A key contribution of this study lies in its methodological design, which advances the empirical analysis of environmental innovation in several ways. First, the study integrates traditional statistical models (logistic regression and LDA) with a suite of ML classifiers (e.g., random forests, GB, SVMs, ANNs). This dual strategy balances interpretability and predictive power: While logistic regression allows for the estimation of OR and formal hypothesis testing, ML models capture nonlinear patterns and complex interactions that cannot be addressed with linear models alone. Second, the research applies these techniques to a large and heterogeneous multicountry dataset (Flash Eurobarometer 486, covering 16,000 + firms in 39 countries), which presents challenges of variability and complexity. By leveraging ensemble methods and validation techniques (70/30 train-test split), the study mitigates issues of overfitting and generalisability, providing more reliable insights into the determinants of eco-innovation across contexts. Third, the study incorporates PDPs, which offer a transparent interpretation of interaction effects, particularly between firm size and other drivers such as business environment and digital maturity. This approach contributes to the growing field of explainable AI by making ML results more interpretable and actionable for both scholars and policymakers. Finally, by systematically comparing models, the study demonstrates the added value of combining traditional and advanced methods in sustainability research. This methodological innovation provides a replicable framework for future studies investigating binary outcomes—such as adoption of green practices—where conventional statistical techniques alone may overlook critical non-linearities, threshold effects, or context-specific dynamics.

5.4 | Policy Implications

The results of this study highlight significant opportunities to reformulate public policies aimed at promoting environmental innovation within the business sector. The prominent role of digital maturity as a key driver suggests that current digitisation programs require reorientation and greater specificity. Beyond merely facilitating access to technology, policies should explicitly link digital transformation initiatives to sustainability goals by providing sector-specific incentives, technical training and tailored support. For example, subsidies aimed at SMEs to adopt data analysis tools can accelerate eco-innovation, especially in regions with limited resources.

Moreover, the territorial context should be reframed not as a barrier but as a strategic factor in policy design. Rural firms—often stereotyped as lagging behind—demonstrate a stronger propensity to innovate in sustainability, likely due to their close connection with the natural environment and locally rooted social dynamics. This finding calls for targeted policies that acknowledge the innovative potential of rural regions and strengthen it through appropriate infrastructure development and technical support networks.

Conversely, in countries and sectors exhibiting low levels of environmental innovation, structural limitations prevail and cannot be addressed by generic measures alone. In these contexts, interventions must prioritise building institutional capacity, enhancing innovation ecosystems and fostering collaboration between public and private stakeholders. Enhancing the business environment in such areas can serve as a critical lever to stimulate transformative dynamics.

In sum, these findings advocate moving beyond a one-size-fits-all policy approach toward differentiated, evidence-based strategies that integrate digital transformation, sustainability and territorial development in a coherent manner. Furthermore, governments can establish partnerships with local actors to monitor the impact of these policies, ensuring their adaptability to the specific needs of each region.

5.5 | Limitations and Recommendations

Despite its contributions, this study has several limitations. First, the reliance on survey data may introduce response bias, as companies might overstate their sustainability efforts to present a favourable image. Although the Flash Eurobarometer 486 dataset, which covers 16,265 companies in 39 countries, provides broad coverage of firms and their environmental innovations, the cultural and institutional diversity across countries likely increases heterogeneity among SMEs and their innovation practices (Ferraro et al. 2024; Hussain et al. 2024). This variability may affect the generalisability of the results. Furthermore, this survey was not specifically designed to capture constructs such as environmental innovation, digital maturity or territorial dimensions, which limits the depth and precision of the variables analysed. In particular, the business environment was operationalised as a composite index and location as a dichotomous variable, which may reduce sensitivity to capturing complex moderation effects. However, the use of multiple methodologies has mitigated some of this heterogeneity, enhancing the robustness of the findings.

For future research, this model could be replicated within more specific or homogeneous contexts, such as groups of countries with similar institutional frameworks, economic development levels or dominant sectors, to generate more precise and context-sensitive conclusions. This approach would reduce variability that can obscure meaningful patterns and facilitate the identification of sectoral or regional dynamics that may be diluted in broader samples.

Extending the analysis to regions with substantially different regulatory systems, governance models and business cultures, particularly outside Europe, would provide critical insights into the external validity of the model. Future studies could also examine how gender diversity on boards of directors (e.g., Saleh and Maigoshi 2024; Saleh et al. 2025) influences the adoption of environmental innovation practices by providing diverse perspectives that enhance strategic decision-making in varied regulatory and cultural contexts. This is particularly relevant in emerging Asian economies, where gender diversity has been shown to positively moderate the relationship between ESG and environmental sustainability. Such research would allow testing the stability of observed relationships and exploring variations in the drivers of environmental innovation influenced by alternative institutional or cultural contexts. Together, these complementary approaches—deepening understanding in homogeneous settings and testing robustness across diverse environments—would advance a more nuanced, robust and contextually grounded theory of environmental innovation.

6 | Conclusions

This study analysed how firm location, business environment and digital maturity influence environmental innovation, as well as the moderating role of firm size in these relationships. The results indicate that geographic location significantly impacts eco-innovation, with rural firms demonstrating a higher propensity to innovate, likely driven by unique environmental challenges and a closer connection to natural resources. This finding reinforces the view that territorial context shapes innovation frameworks and that rural areas can serve as fertile grounds for sustainability.

A favourable business environment further increases the likelihood of environmental innovation, particularly where institutional pressures, market demand and collaborative opportunities align. These findings suggest that external conditions not only influence but actively enable firms' innovative capabilities when supported by sufficient internal resources.

Digital maturity emerges as a crucial factor, enhancing firms' abilities to manage information, automate processes and identify opportunities for environmental improvement through technologies such as IoT and AI. This underscores digital transformation as a direct driver of eco-innovation and a central strategic asset.

Regarding firm size, the results indicate that it does not moderate the relationship between location and environmental innovation, suggesting that territorial influence operates across organisations of all scales. Instead, size amplifies the positive effects of business environment and digital maturity, particularly benefiting larger firms with greater resources to leverage these conditions. Therefore, firm size functions more as a capacity multiplier than as a direct determinant of eco-innovation.

Overall, these findings provide an integrated, contextualised understanding of the drivers behind environmental innovation. The study contributes to both academic and practical debates by demonstrating that eco-innovation depends on a combination of structural and organisational factors, which should be considered when designing business strategies and public policies tailored to diverse territories and firm profiles.

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References

Arimura, T. H., N. Darnall, and H. Katayama. 2011. "Is ISO 14001 a Gateway to More Advanced Voluntary Action? The Case of Green Supply Chain Management." *Journal of Environmental Economics and Management* 61, no. 2: 170–182. https://doi.org/10.1016/j.jeem.2010.11.003.

Asiaei, K., N. G. O'Connor, O. Barani, and M. Joshi. 2023. "Green Intellectual Capital and Ambidextrous Green Innovation: the Impact on Environmental Performance." *Business Strategy and the Environment* 32, no. 1: 369–386. https://doi.org/10.1002/bse.3136.

Barbieri, N., F. Perruchas, and D. Consoli. 2020. "Specialization, Diversification, and Environmental Technology Life Cycle." *Economic Geography* 96: 161–186. https://doi.org/10.1080/00130095.2020.1721279.

Barney, J. 1991. "Firm Resources and Sustained Competitive Advantage." *Journal of Management* 17, no. 1: 99–120. https://doi.org/10.1177/014920639101700108.

Barr, S. 2004. "What We Buy, What We Throw Away and How We Use Our Voice: Sustainable Household Waste Management in the UK." *Sustainable Development* 12, no. 1: 32–44. https://doi.org/10.1002/sd.226.

Battisti, M., and M. Perry. 2011. "Walking the Talk? Environmental Responsibility From the Perspective of Small-Business Owners." *Corporate Social-Responsibility and Environmental Management* 18, no. 3: 172–185. https://doi.org/10.1002/csr.266.

Beier, G., S. Niehoff, T. Ziems, and B. Xue. 2017. "Sustainability Aspects of a Digitalized Industry—a Comparative Study From China and Germany." *International Journal of Precision Engineering and Manufacturing-Green Technology* 4, no. 2: 227–234. https://doi.org/10.1007/s40684-017-0028-8.

Berenguer, J., J. A. Corraliza, and R. Martín. 2005. "Rural-Urban Differences in Environmental Concern, Attitudes, and Actions." *European Journal of Psychological Assessment: Official Organ of the European Association of Psychological Assessment* 21, no. 2: 128–138. https://doi.org/10.1027/1015-5759.21.2.128.

Berger, K., R. J. Baumgartner, M. Weinzerl, J. Bachler, and J.-P. Schöggl. 2023. "Factors of Digital Product Passport Adoption to Enable Circular Information Flows Along the Battery Value Chain." *Procedia CIRP* 116: 528–533. https://doi.org/10.1016/j.procir.2023.02.089.

Berrone, P., A. Fosfuri, L. Gelabert, and L. R. Gomez-Mejia. 2013. "Necessity as the Mother of "Green" Inventions: Institutional Pressures and Environmental Innovations." *Strategic Management Journal* 34, no. 8: 891–909. https://doi.org/10.1002/smj.2041.

Brem, A., P. Nylund, and E. Viardot. 2020. "The Impact of the 2008 Financial Crisis on Innovation: a Dominant Design Perspective." *Journal of Business Research* 110: 360–369. https://doi.org/10.1016/j.jbusres.2020.01.048.

Cerchione, R., R. Passaro, and V. Sicardi. 2025. "Do No Significant Harm (DNSH) Principle in Corporate Sustainability Strategies: Towards a Methodological Framework." *Corporate Social-Responsibility and Environmental Management.* 32: 7528–7552. https://doi.org/10.1002/csr.70070.

Cheng, X., K. Chen, and Y. Su. 2023. "Green Innovation in Oil and Gas Exploration and Production for Meeting the Sustainability Goals." *Resources Policy* 87: 104315. https://doi.org/10.1016/j.resourpol.2023.104315.

Chesbrough, H. W. 2003. *Open Innovation: the New Imperative for Creating and Profiting From Technology.* Harvard Business School Press.

Cooke, P. 1992. "Regional Innovation Systems: Competitive Regulation in the New Europe." *Geoforum* 23, no. 3: 365–382. https://doi.org/10.1016/0016-7185(92)90048-9.

Crossley, R. M., M. H. Elmagrhi, and C. G. Ntim. 2021. "Sustainability and Legitimacy Theory: the Case of Sustainable Social and Environmental Practices of Small and Medium-Sized Enterprises." *Business Strategy and the Environment* 30, no. 8: 3740–3762. https://doi.org/10.1002/bse.2837.

Cruz, E. F., and A. M. R. da Cruz. 2020. "Using Blockchain to Implement Traceability on Fishery Value Chain." *ICSOFT* 1195: 501–508.

D'Agostino, L. M., and R. Moreno. 2019. "Green Regions and Local Firms' Innovation." *Papers in Regional Science* 98, no. 4: 1585–1608. https://doi.org/10.1111/pirs.12427.

Dangelico, R. M., D. Pujari, and P. Pontrandolfo. 2017. "Green Product Innovation in Manufacturing Firms: a Sustainability-Oriented Dynamic Capability Perspective." *Business Strategy and the Environment* 2: 490–506. https://doi.org/10.1002/bse.1932.

Darmandieu, A., C. Garcés-Ayerbe, A. Renucci, and P. Rivera-Torres. 2022. "How Does It Pay to be Circular in Production Processes? Eco-Innovativeness and Green Jobs as Moderators of a Cost-Efficiency Advantage in European Small and Medium Enterprises." *Business Strategy and the Environment* 31, no. 3: 1184–1203. https://doi.org/10.1002/bse.2949.

De Giuli, M. E., D. Grechi, and A. Tanda. 2024. "What Do We Know About ESG and Risk? A Systematic and Bibliometric Review." *Corporate Social-Responsibility and Environmental Management* 31, no. 2: 1096–1108. https://doi.org/10.1002/csr.2624.

de Souza Barbosa, A., M. C. B. C. da Silva, L. B. da Silva, S. N. Morioka, and V. F. de Souza. 2023. "Integration of Environmental, Social, and Governance (ESG) Criteria: Their Impacts on Corporate Sustainability Performance." *Humanities & Social Sciences Communications* 10, no. 1: 410. https://doi.org/10.1057/s41599-023-01919-0.

Dimakopoulou, A. G., N. Chatzistamoulou, K. Kounetas, and K. Tsekouras. 2023. "Environmental Innovation and R&D Collaborations: Firm Decisions in the Innovation Efficiency Context." *Journal of Technology Transfer* 48, no. 4: 1176–1205. https://doi.org/10.1007/s10961-022-09963-9.

Donaldson, L. 2001. *The Contingency Theory of Organizations*. Sage.

Edu, A. S., E. Ofosuhene, D. Q. Agozie, B. A. Gyamfi, and S. A. Asongu. 2024. "Optimizing Sustainable Resource Efficiency: A Fuzzy-Set Qualitative Comparative Analysis of Sustainable Practices in SMEs." *Business Strategy and the Environment*. 34: 2799–2812. https://doi.org/10.1002/bse.4125.

European Commission. 2020. *Flash Eurobarometer 486 (SMEs, Start-Ups, Scale-Ups and Entrepreneurship)*. Cologne: GESIS Data Archive ZA7637 Data file Version 2.0. 0.

Feng, H., F. Wang, G. Song, and L. Liu. 2022. "Digital Transformation on Enterprise Green Innovation: Effect and Transmission Mechanism." *International Journal of Environmental Research and Public Health* 19, no. 17: 10614. https://doi.org/10.3390/ijerph191710614.

Feroz, A. K., H. Zo, and A. Chiravuri. 2021. "Digital Transformation and Environmental Sustainability: a Review and Research Agenda." *Sustainability* 13, no. 3: 1530. https://doi.org/10.3390/su13031530.

Ferraro, G., R. Passaro, I. Quinto, and A. Thomas. 2024. "The Process Supporting the Emergence of the Environmental Innovation Capabilities Within Small Businesses: an Empirical Investigation." *Business Strategy and the Environment*. 34: 1027–1042. https://doi.org/10.1002/bse.4015.

Freeman, R. E. 2010. *Strategic Management: a Stakeholder Approach*. Cambridge University Press.

Galliano, D., S. Nadel, and P. Triboulet. 2023. "The Geography of Environmental Innovation: a Rural/Urban Comparison." *Annals of Regional Science* 71, no. 1: 27–59. https://doi.org/10.1007/s00168-022-01149-3.

Ghisetti, C., A. Marzucchi, and S. Montresor. 2015. "The Open Eco-Innovation mode. An Empirical Investigation of Eleven European Countries." *Research Policy* 44: 1080–1093. https://doi.org/10.1016/j.respol.2014.12.001.

Gnyawali, D. R., and B.-J. (R.) Park. 2011. "Co-Opetition Between Giants: Collaboration With Competitors for Technological Innovation." *Research Policy* 40, no. 5: 650–663. https://doi.org/10.1016/j.respol.2011.01.009.

Gollhardt, T., S. Halsbenning, A. Hermann, A. Karsakova, and J. Becker 2020. "Development of a Digital Transformation Maturity Model for IT Companies." *2020 IEEE* 22nd Conference on Business Informatics (CBI), 1, 94–103. https://doi.org/10.1109/CBI49978.2020.00018.

Grillitsch, M., and M. Nilsson. 2015. "Innovation in Peripheral Regions: Do Collaborations Compensate for a Lack of Local Knowledge Spillovers?" *Annals of Regional Science* 54: 299–321. https://doi.org/10.1007/s00168-014-0655-8.

Hall, B. H., and D. Harhoff. 2012. "Recent Research on the Economics of Patents." *Annual Review of Economics* 4, no. 1: 541–565. https://doi.org/10.1146/annurev-economics-080511-111008.

Hall, B. H., and J. Lerner 2009. "The Financing of R&D and Innovation." *NBER Working Paper Series*, 15325-. https://doi.org/10.3386/w15325.

Han, Y., C. Pan, and F. Jin. 2023. "Does the Improvement of the Business Environment Improve the Innovation Efficiency of Enterprises? Evidence From the Listed Companies in China." *Sustainability* 15, no. 14: 11424. https://doi.org/10.3390/su151411424.

Hansen, T., and L. Coenen. 2015. "The Geography of Sustainability Transitions: Review, Synthesis and Reflections on an Emergent Research Field." *Environ Innov Soc Transit* 17: 92–109. https://doi.org/10.1016/j.eist.2014.11.001.

Horbach, J., and C. Rammer. 2018. "Energy Transition in Germany and Regional Spill-Overs: the Diffusion of Renewable Energy in Firms." *Energy Policy* 121: 404–414. https://doi.org/10.1016/j.enpol.2018.06.042.

Hou, D., Z. Liu, R. M. A. Zahid, and U. S. Maqsood. 2024. "ESG Dynamics in Modern Digital World: Empirical Evidence From Firm Life-Cycle Stages." *Environment, Development and Sustainability*. 27: 12325–12350. https://doi.org/10.1007/s10668-023-04425-0.

Hussain, T., A. A. Tunyi, and G. Areneke. 2024. "Environmental Innovation and Takeover Performance." *Business Strategy and the Environment* 33, no. 7: 6586–6615. https://doi.org/10.1002/bse.3822.

Iammarino, S. 2011. "Regional Innovation and Diversity." In *Handbook of Regional Innovation and Growth*, edited by P. Cooke and B. Asheim. Edward Elgar.

Jaffe, A. B., and K. Palmer. 1997. "Environmental Regulation and Innovation: A Panel Data Study." *Review of Economics and Statistics* 79, no. 4: 610–619. https://doi.org/10.1162/003465397557196.

Jardak, M. K., and S. Ben Hamad. 2022. "The Effect of Digital Transformation on Firm Performance: Evidence From Swedish Listed Companies." *Journal of Risk Finance* 23, no. 4: 329–348. https://doi.org/10.1108/JRF-12-2021-0199.

Kemp, R., and P. Pearson. 2007. "Final Report MEI Project About Measuring Eco-Innovation." *UM Merit, Maastricht* 10, no. 2: 1–120.

Kim, Y. 2015. "Environmental, Sustainable Behaviors and Innovation of Firms During the Financial Crisis." *Business Strategy and the Environment* 24, no. 1: 58–72. https://doi.org/10.1002/bse.1811.

Kotani, K., and M. Kakinaka. 2017. "Some Implications of Environmental Regulation on Social Welfare Under Learning-by-Doing of Eco-Products." *Environmental Economics and Policy Studies* 19: 121–149. https://doi.org/10.1007/s10018-015-0140-3.

Kyriakopoulos, P. 2024. "Revisiting Research on Firm-Level Innovation in Rural Areas: a Systematic Literature Review and Future Research

Directions." *Journal of Rural Studies* 111: 103437. https://doi.org/10.1016/j.jrurstud.2024.103437.

Liu, F., W. Huang, J. Zhang, and M. Fang. 2024. "Corporate Social Responsibility in Family Business: Using Machine Learning to Uncover Who Is Doing Good." *Technology in Society* 76: 102453. https://doi.org/10.1016/j.techsoc.2024.102453.

Madrid-Guijarro, A., and A. Duréndez. 2024. "Sustainable Development Barriers and Pressures in SMEs: the Mediating Effect of Management Commitment to Environmental Practices." *Business Strategy and the Environment* 33, no. 2: 949–967. https://doi.org/10.1002/bse.3537.

Mahmood, N., Y. Zhao, Q. Lou, and J. Geng. 2022. "Role of Environmental Regulations and Eco-Innovation in Energy Structure Transition for Green Growth: Evidence From OECD." *Technological Forecasting and Social Change* 183: 121890. https://doi.org/10.1016/j.techfore.2022.121890.

Malerba, F. 2010. *Knowledge Intensive Entrepreneurship and Innovation Systems: Evidence From Europe*. Vol. 48, pp. xxiii–xxiii. 1st ed. Routledge. https://doi.org/10.4324/9780203857403.

Mansour, M., M. F. Shubita, A. Lutfi, M. W. A. Saleh, and M. Saad. 2024. "Female CEOs and Green Innovation: Evidence From Asian Firms." *Sustainability* 16, no. 21: 9404. https://doi.org/10.3390/su16219404.

Marshall, N. A., C. J. Stokes, N. P. Webb, P. A. Marshall, and A. J. Lankester. 2014. "Social Vulnerability to Climate Change in Primary Producers: a Typology Approach." *Agriculture, Ecosystems & Environment* 186: 86–93. https://doi.org/10.1016/j.agee.2014.01.004.

Mateo, F. W., A. Redchuk, and J. E. Tornillo 2022. "Industry 5.0 and New Business Models in Mining. Adoption Case of Machine Learning to Optimize the Process at a Copper Semi Autogenous Grinding (SAG) Mill." In *Proceedings of the 5th European International Conference on Industrial Engineering and Operations Management, Rome, Italy* (pp. 26–28).

Mikalef, P., J. Krogstie, I. O. Pappas, and P. Pavlou. 2020. "Exploring the Relationship Between Big Data Analytics Capability and Competitive Performance: the mediating Roles of Dynamic and Operational Capabilities." *Information & Management* 57, no. 2: 103169. https://doi.org/10.1016/j.im.2019.05.004.

Molnar, C., T. Freiesleben, G. König, et al. 2023. "Relating the Partial Dependence Plot and Permutation Feature Importance to the Data Generating Process." In *Explainable Artificial Intelligence*, vol. 1901, 456–479. Springer. https://doi.org/10.1007/978-3-031-44064-9_24.

Morea, D., S. Fortunati, F. Cappa, and R. Oriani. 2023. "Corporate Social Responsibility as a Catalyst of Circular Economy? A Case Study Perspective in Agri-Food." *Journal of Knowledge Management* 27, no. 7: 1787–1809. https://doi.org/10.1108/JKM-06-2022-0451.

Nambisan, S. 2017. "Digital Entrepreneurship: Toward a Digital Technology Perspective of Entrepreneurship." *Entrepreneurship Theory and Practice* 41, no. 6: 1029–1055. https://doi.org/10.1111/etap.12254.

Nayal, K., S. Kumar, R. D. Raut, M. M. Queiroz, P. Priyadarshinee, and B. E. Narkhede. 2022. "Supply Chain Firm Performance in Circular Economy and Digital Era to Achieve Sustainable Development Goals." *Business Strategy and the Environment* 31, no. 3: 1058–1073. https://doi.org/10.1002/bse.2935.

North, D. C. 1990. "*Institutions, Institutional Change and Economic Performance* (1st. pub., 24 print.)." University of Cambridge.

Ochoa-Urrego, R. L., and J. I. Peña-Reyes 2021. "Digital Maturity Models: a Systematic Literature Review." Digitalization: Approaches, Case Studies, and Tools for Strategy, Transformation and Implementation, 71–85.

Ottman, J. 2017. *The New Rules of Green Marketing: Strategies, Tools, and Inspiration for Sustainable branding*. Routledge.

Pérez-De-Lema, D. G., P. B. Hansen, A. Madrid-Gujjarro, and J. L. Silva-Santos. 2019. "Influence of the Business Environment in the Dynamics of Innovation and in the Performance of SMEs." *International Journal of Innovation Management* 23, no. 5: 1950044. https://doi.org/10.1142/S1363919619500440.

Pigola, A., P. R. Da Costa, L. C. Carvalho, L. F. D. Silva, C. T. Kniess, and E. A. Maccari. 2021. "Artificial Intelligence-Driven Digital Technologies to the Implementation of the Sustainable Development Goals: a Perspective from Brazil and Portugal." *Sustainability* 13, no. 24: 13669. https://doi.org/10.3390/su132413669.

Popp, D. 2020. "Promoting Clean Energy Innovation at the State and Local Level." *Agricultural and Resource Economics Review* 49, no. 2: 360–373. https://doi.org/10.1017/age.2020.15.

Porter, M. E., and C. van der Linde. 1995. "Green and Competitive: Ending the Stalemate." *Harvard business review* 73, no. 5: 120–137.

Putnam, R. D. 2000. *Bowling Alone: the Collapse and Revival of American Community*. Simon and Schuster.

Ranghino, F. 2019. "Industry 4.0 and Environmental Sustainability: Good or Bad News." Ambienta Sustainability Lens, 1–8.

Rashidi, K., A. Noorizadeh, D. Kannan, and K. Cullinane. 2020. "Applying the Triple Bottom Line in Sustainable Supplier Selection: A Meta-Review of the State-of-the-Art." *Journal of Cleaner Production* 269: 122001. https://doi.org/10.1016/j.jclepro.2020.122001.

Rath, S., A. Sinha, and S. Mishra. 2024. "Digital Transformation and Environmental Sustainability: A Review and Research Agenda." *Sustainability* 16, no. 24: 11079. https://doi.org/10.3390/su162411079.

Saleh, M. W. A., S. M. Alshdaifat, M. F. Shubita, M. Mansour, and A. Lutfi. 2025. "Gender Diversity and Environmental, Social, and Governance: Unlocking Solutions to Corporate Risk." *Business Strategy & Development* 8, no. 1: 1–13. https://doi.org/10.1002/bsd2.70097.

Saleh, M. W. A., and Z. S. Maigoshi. 2024. "The Nexus of ESG and Environmental Sustainability: Does Gender Diversity Make a Difference in Asian Companies?" *Environment, Development and Sustainability* 27: 13793–13813. https://doi.org/10.1007/s10668-024-04498-5.

Saleh, M. W. A., and M. Mansour. 2024. "Is Audit Committee Busyness Associated With Earnings Management? The Moderating Role of Foreign Ownership." *Accounting Research Journal* 37, no. 1: 80–97. https://doi.org/10.1108/ARJ-04-2023-0106.

Scott, W. R. 1995. *Institutions and Organizations*. Sage.

Scott, W. R. 2008. "Approaching Adulthood: the Maturing of Institutional Theory." *Theory and Society* 37, no. 5: 427–442. https://doi.org/10.1007/s11186-008-9067-z.

Sharif, A., S. Kocak, H. H. A. Khan, G. Uzuner, and S. Tiwari. 2023. "Demystifying the Links Between Green Technology Innovation, Economic Growth, and Environmental Tax in ASEAN-6 Countries: the Dynamic Role of Green Energy and Green Investment." *Gondwana Research* 115: 98–106. https://doi.org/10.1016/j.gr.2022.11.010.

Teece, D. J. 2007. "Explicating Dynamic Capabilities: the Nature and Microfoundations of (Sustainable) Enterprise Performance." *Strategic Management Journal* 28, no. 13: 1319–1350. https://doi.org/10.1002/smj.640.

Trantopoulos, K., M. Woerter, and G. von Krogh. 2024. "Open Innovation During the 2008 Financial Crisis." *Industry and Innovation* 31, no. 2: 159–182. https://doi.org/10.1080/13662716.2023.2228724.

Venkatesan, L. 2020. "The Effect of Digital Maturity and Entrepreneurial Agility on Firm Performance in Digital Transformation of Traditional Organisations." ProQuest Dissertations & Theses.

Wang, Y., Y. Yang, C. Fu, Z. Fan, and X. Zhou. 2021. "Environmental Regulation, Environmental Responsibility, and Green Technology Innovation: Empirical Research From China." *PLoS ONE* 16, no. 9: e0257670. https://doi.org/10.1371/journal.pone.0257670.

Westerman, G., D. Bonnet, and A. McAfee. 2014. *Leading Digital: Turning Technology Into Business Transformation*. Harvard Business Press.

Xu, C., G. Sun, and T. Kong. 2024. "The Impact of Digital Transformation on Enterprise Green Innovation." *International Review of Economics & Finance* 90: 1–12. https://doi.org/10.1016/j.iref.2023.11.001.

Yao, Q., H. Tang, F. Boadu, and Y. Xie. 2023. "Digital Transformation and Firm Sustainable Growth: the Moderating Effects of Cross-border Search Capability and Managerial Digital Concern." *Journal of the Knowledge Economy* 14, no. 4: 4929–4953. https://doi.org/10.1007/s13132-022-01083-x.

Zartha Sossa, J. W., O. H. López Montoya, and J. C. Acosta Prado. 2021. "Determinants of a Sustainable Innovation System." *Business Strategy and the Environment* 30, no. 2: 1345–1356. https://doi.org/10.1002/bse.2689.

Zhu, Y., H. Gao, Y. Hu, Q. Ding, and Y. Tang. 2023. "Can Local Environmental Constraints Improve Enterprise's Green Innovation Quality? Evidence From Chinese-Listed Firms." *Environmental Science and Pollution Research International* 30, no. 1: 389–406. https://doi.org/10.1007/s11356-022-22161-2.

Appendix

TABLE A1 | Summary statistics of variables.

	Mean	SD	Range
Environmental innovation	0.221	0.415	0–1
Time since your enterprise first registered	24.738	22.830	1–1021
Exporting activity	0.341	0.474	0–1
Employees, excluding the owners	143.002	938.329	0–1
Located in RuraL	0.103	0.303	0–1
Digital maturity	0.205	0.204	0–1
Business environment	0.350	0.161	0–1
FR—France	0.031	0.173	0–1
BE—Belgium	0.030	0.172	0–1
NL—The Netherlands	0.030	0.172	0–1
DE—Germany	0.031	0.173	0–1
IT—Italy	0.030	0.171	0–1
LU—Luxembourg	0.012	0.110	0–1
DK—Denmark	0.031	0.172	0–1
IE—Ireland	0.029	0.169	0–1
GB—United Kingdom	0.029	0.169	0–1
GR—Greece	0.030	0.171	0–1
ES—Spain	0.031	0.172	0–1
PT—Portugal	0.030	0.171	0–1
FI—Finland	0.031	0.174	0–1
SE—Sweden	0.031	0.173	0–1
AT—Austria	0.031	0.173	0–1
CY—Cyprus (Republic)	0.012	0.111	0–1
CZ—Czech Republic	0.031	0.173	0–1
EE—Estonia	0.030	0.170	0–1
HU—Hungary	0.031	0.173	0–1
LV—Latvia	0.031	0.173	0–1
LT—Lithuania	0.031	0.173	0–1
MT—Malta	0.013	0.111	0–1
PL—Poland	0.031	0.173	0–1
SK—Slovakia	0.030	0.172	0–1
SI—Slovenia	0.031	0.173	0–1
BG—Bulgaria	0.030	0.171	0–1
RO—Romania	0.031	0.174	0–1
TR—Turkey	0.018	0.134	0–1
HR—Croatia	0.031	0.173	0–1
MK—Makedonia	0.013	0.111	0–1
RS—Serbia	0.012	0.111	0–1
NO—Norway	0.019	0.135	0–1
IS—Iceland	0.013	0.111	0–1
JP—Japan	0.018	0.131	0–1
US—USA	0.030	0.172	0–1
BR—Brazil	0.021	0.144	0–1
BA—Bosnia and Herzegovina	0.013	0.111	0–1
RS-KM—Kosovo	0.013	0.111	0–1
CA—Canada	0.031	0.173	0–1
B—Mining and quarrying	0.006	0.075	0–1
C—Manufacturing	0.195	0.396	0–1
D—Electricity, gas, steam and air conditioning supply	0.006	0.077	0–1
E—Water supply, sewerage, waste management/remediation activities	0.010	0.100	0–1
F—Construction	0.097	0.296	0–1
G—Wholesale and retail trade, repair of motor vehicles and	0.277	0.448	0–1
H—Transportation and storage	0.057	0.232	0–1
I—Accommodation and food service activities	0.055	0.229	0–1
J—Information and communication	0.038	0.192	0–1
K—Financial and insurance activities	0.021	0.145	0–1
L—Real estate activities	0.023	0.150	0–1
M—Professional, scientific and technical activities	0.094	0.292	0–1
N—Administrative and support service activities	0.044	0.205	0–1
P—Education	0.022	0.148	0–1
Q—Human health and social work activities	0.037	0.189	0–1
R—Arts, entertainment and recreation	0.017	0.128	0–1