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Artificial intelligence investments and environmental quality: Evidence from carbon emissions, ecological footprint, and sustainable development performance

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ABSTRACT

This study examines the impact of artificial intelligence investments on environmental sustainability by simultaneously considering three complementary environmental indicators: carbon emissions, ecological footprint, and sustainable development scores. The analysis employs a panel dataset covering the 19 countries with the highest levels of artificial intelligence investments over the 2012-2023 period. Long-run relationships among the variables are confirmed using the Westerlund-Edgerton Bootstrap cointegration test. Long-run coefficients are estimated using the Panel Corrected Standard Errors (PCSE), Seemingly Unrelated Regression (SUR), and Driscoll-Kraay estimators, while causal relationships are examined through the Dumitrescu-Hurlin panel causality test. The empirical findings reveal that artificial intelligence investments significantly increase carbon emissions and the ecological footprint, while significantly reducing sustainable development scores. Moreover, the results demonstrate that the environmental effects of artificial intelligence are not unidirectional and cannot be evaluated independently of countries' energy infrastructure and environmental policies. The findings are expected to provide important empirical evidence for policymakers, public authorities, and decision-makers responsible for designing environmental, energy, and digital transformation policies.

1. Introduction

Artificial intelligence (AI) has become one of the most strategic technologies of the digital economy in recent years, fundamentally transforming production systems, energy management, transportation, and environmental monitoring. Advances in big data analytics, machine learning, and deep learning algorithms have positioned AI as one of the key technological components that accelerates decision-making processes, optimizes resource utilization, and improves operational efficiency. With the rapid expansion of Industry 4.0, smart cities, and digital transformation initiatives, AI investments have become not only an important driver of economic growth but also a significant component of environmental sustainability policies (Alotaibi and Nassif 2024; Popescu et al. 2024).

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From the perspective of environmental sustainability, AI influences environmental outcomes through two distinct mechanisms. The first mechanism relates to the contribution of AI to environmental management. AI-enabled systems can forecast energy demand in real time, optimize production processes, improve waste management, and predict environmental risks with a high degree of accuracy. Likewise, smart electricity grids, intelligent transportation systems, and industrial automation applications can enhance energy efficiency and reduce greenhouse gas emissions (Ding et al. 2024; Miller et al. 2024; Hua et al. 2025). Consequently, AI is widely regarded as one of the key technologies supporting the transition toward a low-carbon economy.

However, the environmental implications of AI are not limited to the efficiency gains it provides. The rapid expansion of large language models, cloud computing systems, and high-performance computing infrastructure has substantially increased the electricity consumption of data centers. The intensive computational capacity required to operate AI applications may increase carbon emissions, particularly in countries where electricity generation continues to rely heavily on fossil fuels. Furthermore, the growing demand for advanced semiconductor manufacturing, electronic hardware, and critical minerals has intensified pressure on natural resource utilization. As a result, the concept of Green Artificial intelligence has gained increasing attention in recent years, emphasizing that AI systems should not only be used to address environmental challenges but should also be developed in ways that reduce energy consumption and minimize carbon footprints throughout their entire life cycle (Bolón-Canedo et al. 2024).

Artificial intelligence investments and their impact on environmental sustainability can be explained through different theoretical perspectives. Socio-Technical Systems Theory argues that technological transformation is not solely driven by technical innovations but rather constitutes a holistic process shaped by the interaction of institutional structures, energy systems, regulatory policies, and social actors (Geels 2004). Within this framework, the environmental consequences of artificial intelligence technologies cannot be evaluated independently of countries' energy infrastructure, digital transformation capacity, and governance mechanisms. Similarly, Ecological Modernization Theory suggests that economic growth and environmental sustainability can be achieved simultaneously when technological innovations are supported by effective environmental policies and institutional regulations (Mol and Spaargaren 2000). The recently emerging Green Artificial Intelligence approach further emphasizes that it is not sufficient to use artificial intelligence solely to address environmental problems; rather, algorithms, data centers, and digital infrastructure should also be designed to minimize energy consumption and carbon footprints throughout their life cycles (Schwartz et al. 2020; Bolón-Canedo et al. 2024). Meanwhile, Digital Transformation Theory posits that artificial intelligence investments can promote sustainable development by reshaping production processes, energy management, and resource utilization; however, the environmental benefits of this transformation depend on the integration of digital infrastructure with renewable energy systems, environmental governance, and sustainable production models (Vial 2021). Therefore, when these theoretical perspectives are considered together, they suggest that the environmental effects of artificial intelligence investments are not linear but rather represent a multidimensional process shaped not only by technological capacity but also by the effectiveness of energy transition, institutional quality, and environmental policies.

This theoretical framework suggests that the environmental effects of AI investments are not unidirectional. While AI can improve environmental quality by increasing energy efficiency when supported by appropriate energy infrastructure, environmental regulations, and technological transformation policies, it may also intensify environmental pressures through rising energy demand, the rapid expansion of data centers, and increased natural resource consumption. Therefore, evaluating the environmental implications of AI requires a comprehensive perspective that considers not only carbon emissions but also multiple dimensions of environmental sustainability, including natural resource utilization and sustainable development performance.

The primary objective of this study is to examine the impact of artificial intelligence investments on environmental sustainability by simultaneously considering three complementary environmental indicators: carbon emissions, ecological footprint, and sustainable development scores. To this end, annual data for the 19 countries with the highest levels of artificial intelligence investments over the 2012-2023 period are analyzed. Long-run coefficients are estimated using the PCSE, SUR, and Driscoll-Kraay estimators. In addition, long-run relationships among the variables are examined using the Westerlund-Edgerton Bootstrap Cointegration test, while causal relationships are investigated through the Dumitrescu-Hurlin panel causality approach. Accordingly, the study aims to provide a comprehensive assessment of the effects of artificial intelligence investments on environmental sustainability by employing multiple environmental indicators together with complementary econometric techniques.

The main motivation of this study stems from the lack of consensus in the existing literature regarding the environmental consequences of artificial intelligence investments. On the one hand, artificial intelligence is argued to improve environmental quality by increasing energy efficiency, optimizing production processes, and facilitating the diffusion of green technologies. On the other hand, the rapid expansion of data centers, cloud computing infrastructure, and computationally intensive artificial intelligence systems is considered to increase energy consumption and natural resource use, thereby intensifying environmental pressures. Therefore, evaluating the actual environmental effects of artificial intelligence investments through multiple environmental indicators has become increasingly important. Furthermore, a considerable proportion of the existing studies evaluate environmental quality using only a single indicator, such as carbon emissions or the ecological footprint, while giving limited attention to multidimensional assessments that also incorporate sustainable development performance. Consequently, there is a need to assess the environmental implications of artificial intelligence investments simultaneously across different dimensions of environmental sustainability. The findings of this study are expected to provide important implications for policymakers in the formulation of environmental, energy, and digital transformation policies. Identifying the multidimensional effects of artificial intelligence investments on environmental quality may contribute to designing digital transformation strategies that are better aligned with environmental sustainability objectives. In particular, the study is expected to provide empirical evidence for decision-makers regarding the integration of artificial intelligence infrastructure with renewable energy systems, the improvement of energy efficiency, the promotion of low-carbon digital technologies, and the development of artificial intelligence policies that support sustainable development goals.

This study consists of eight sections. The introduction presents the theoretical background, objective, motivation, and overall framework of the study. The second section reviews the relevant literature. The third and fourth sections describe the dataset and methodology. The fifth section presents the empirical findings, while the sixth section discusses the results in light of the existing literature. The seventh section provides policy implications based on the findings. Finally, the last section evaluates the main conclusions of the study, discusses its limitations, and offers suggestions for future research.

2. Literature review

Recent advances in artificial intelligence (AI) technologies have created a new research stream within the environmental sustainability literature. Nevertheless, no consensus has yet emerged regarding the environmental consequences of AI. One group of scholars considers AI a transformative technology capable of enhancing energy efficiency, optimizing resource utilization, and reducing carbon emissions, whereas another argues that AI systems accelerate environmental degradation due to their enormous computational requirements and the associated increase in energy consumption. Consequently, the net impact of AI investments on environmental quality has become one of the most debated issues in the contemporary environmental economics and sustainable development literature.

The earliest strand of this literature primarily focuses on the role of AI in environmental monitoring and management. These studies consistently demonstrate that AI provides substantial advantages for policymakers in identifying and managing environmental challenges. Alotaibi and Nassif (2024), Olawade et al. (2024), and Popescu et al. (2024) show that AI-supported environmental monitoring systems enable real-time observation of air, water, and soil quality and, when integrated with Internet of Things (IoT) technologies, significantly improve the early prediction of environmental risks. Similarly, Kumari and Pandey (2023), Fan et al. (2023), and Nassef et al. (2023) argue that AI represents a transformative tool for climate change mitigation, environmental modeling, and sustainable energy management. However, the majority of these studies are conceptual discussions or application-oriented case studies rather than empirical analyses evaluating the macroeconomic consequences of AI investments. Consequently, although the existing literature provides valuable insights into how AI can be utilized in environmental management, it does not sufficiently explain the long-term contribution of AI investments to countries' environmental performance.

Another major research stream examines the relationship between AI and energy systems, primarily from the perspective of energy efficiency. Khanmohammadi et al. (2022), Ding et al. (2024), Zhang et al. (2023), Miller et al. (2024), Hua et al. (2025), and Alatalo et al. (2025) demonstrate that AI applications optimize energy consumption and generate considerable efficiency gains across buildings, transportation systems, and energy infrastructure. Likewise, Delanoë et al. (2023) report that AI models can significantly reduce carbon emissions, while de Sousa Sampaio et al. (2025) show that AI-based calculation models successfully reduce emissions from heavy-duty transport. Nevertheless, because most of these studies are conducted at the sectoral or firm level, the extent to which their findings can be generalized to national environmental performance remains uncertain. Moreover, the literature has yet to reach a consensus regarding whether the efficiency gains generated by AI are sufficient to offset the rapidly increasing energy demand associated with expanding AI infrastructure.

Empirical studies investigating the relationship between AI investments and carbon emissions have produced mixed findings. Zhao et al. (2024), Dong et al. (2024), Cao et al. (2025), Chen et al. (2026), Zhou et al. (2024), Zhang et al. (2026), and Jin et al. (2026) conclude that AI contributes to carbon emission reduction by improving energy efficiency, accelerating green technological development, and optimizing production processes. Similarly, Gaur et al. (2023) argue, from a systems theory perspective, that AI constitutes a strategic instrument for carbon management, while Melguizo et al. (2026) demonstrate that the interaction between AI and renewable energy enhances environmental performance. In contrast, Xu and Song (2023), Luo and Feng (2024), Zhou et al. (2026), and Abd El-Aal (2025) argue that the environmental effects of AI are not linear but vary depending on countries' technological development, energy mix, income level, and production structure. In particular, the substantial electricity consumption associated with data centers and high-performance computing infrastructure may offset the emission-reducing effects of AI in certain countries. These findings suggest that the environmental consequences of AI should be evaluated not only from the perspective of technological advancement but also in conjunction with national energy systems and environmental policy frameworks.

An emerging concept within the literature is Green Artificial Intelligence. Bolón-Canedo et al. (2024) argue that AI should not only be employed to solve environmental problems but should itself be developed in a more energy-efficient and environmentally sustainable manner by reducing the energy consumption and carbon footprint of AI algorithms. This perspective highlights the dual nature of AI in the context of sustainability. While AI facilitates the solution of environmental challenges, its own energy requirements may simultaneously generate new environmental pressures. Accordingly, the growing consensus in the literature suggests that the environmental impact of AI should be evaluated jointly with energy efficiency, renewable energy deployment, and environmental governance rather than solely through technological capability.

Beyond carbon emissions, recent studies have increasingly investigated the relationship between AI and environmental sustainability from the perspective of the ecological footprint. Since the ecological footprint accounts not only for carbon emissions but also for natural resource consumption and pressure on biocapacity, it is considered a more comprehensive indicator of environmental sustainability. In this context, Balcı et al. (2026) demonstrate that AI combined with educational investments can reduce the ecological footprint, while Rahman et al. (2026) show that AI applications and energy innovation decrease ecological footprints in G7 countries by reducing dependence on fossil fuels. Similarly, van der Woude et al. (2025) report that AI techniques substantially improve the prediction accuracy of biocapacity and ecological footprints, whereas Dere (2026) emphasizes the strategic role of AI in developing sustainable production systems through carbon footprint management. Conversely, Balsalobre-Lorente et al. (2026) argue that the influence of AI on ecological footprints depends on environmental policy effectiveness and energy-related institutional factors, particularly nuclear energy utilization. These findings indicate that although AI has the potential to enhance ecological sustainability, its effectiveness cannot be evaluated independently of countries' energy transition processes and environmental governance capacity.

The relationship between AI and the Sustainable Development Goals (SDGs) has also attracted increasing scholarly attention. Most studies extend beyond environmental indicators and examine AI's broader economic and social contributions to sustainable development. Maghsoudi et al. (2025)

demonstrate that governance mechanisms play a decisive role in utilizing AI to achieve the SDGs in both developed and developing countries. Spagnuolo et al. (2025) report that AI improves SDG performance among European state-owned enterprises, whereas Varriale et al. (2026) identify AI as a major catalyst for achieving sustainable development through technological networks. Likewise, Fazal et al. (2025) show that AI promotes sustainable development through financial inclusion, while Balasooriya and Sedera (2025) find that organizations whose top management effectively governs AI applications exhibit superior sustainability performance. Similar conclusions emerge in the education literature. Apata et al. (2025) and Jogezai et al. (2026) demonstrate that AI contributes particularly to SDG 4 and SDG 10 in higher education. However, these studies mainly focus on specific SDGs or sectoral applications and rarely investigate the impact of AI on countries' overall SDG performance at the macroeconomic level. Consequently, the effect of AI investments on aggregate sustainable development performance remains largely underexplored.

Another important issue highlighted by the literature is that the environmental effects of AI are neither linear nor universal. Wang et al. (2026) suggest that the relationship between AI and environmental sustainability varies within the framework of the Environmental Kuznets Curve, while Melguizo et al. (2026) identify nonlinear interactions among AI, renewable energy, and carbon emissions. Tithi (2025) reports that the contribution of private AI investments to carbon neutrality depends significantly on the level of financial development. Similarly, Yıldırım (2025) demonstrates that the dynamic relationship between AI and ESG performance evolves over time. Collectively, these findings indicate that the environmental consequences of AI investments cannot be explained without considering countries' institutional quality, energy systems, financial development, and technological capabilities. In other words, AI alone cannot guarantee environmental sustainability; rather, its effectiveness largely depends on complementary economic and institutional conditions.

Overall, the existing literature provides substantial evidence that AI can reduce carbon emissions, improve energy efficiency, decrease ecological footprints, and contribute to achieving the Sustainable Development Goals. Nevertheless, most previous studies focus on specific industries, individual environmental indicators, or particular groups of countries. Environmental performance has generally been assessed using either carbon emissions or ecological footprints, whereas sustainable development indicators have typically been examined separately. Moreover, many existing studies are conducted at the firm or sectoral level and make limited use of second-generation panel econometric techniques that account for cross-sectional heterogeneity. Therefore, studies simultaneously examining the effects of AI investments on carbon emissions, ecological footprints, and SDG performance within a unified empirical framework remain scarce. This study seeks to address this gap by providing a multidimensional assessment of the environmental consequences of AI investments and contributes to the existing literature both theoretically and empirically through a panel data analysis covering both developed and developing economies.

3. Methodology

3.1. Data and model

This study analyzes the impact of AI investments on environmental quality indicators specifically carbon emissions, ecological footprint, and sustainable development score while controlling for financial development, capital accumulation, and economic growth. Annual data from 2012-2023 are used, covering 19 countries with the highest levels of AI investment globally: Australia, Brazil, China, Denmark, Finland, France, Germany, India, Ireland, Japan, South Korea, Malaysia, Poland, Spain, Sweden, the United Kingdom, the United States, Israel, and Italy. The variables used in the study are presented in Table 1.

Table 1 presents the variables used in the study, their abbreviations, measurement methods, and data sources. Three main dependent variables representing environmental quality were used in the study. The first is carbon emissions, measured in metric tons of CO_2 emissions released into the atmosphere by countries, and the data was obtained from the World Bank's World Development Indicators database. The second environmental indicator is ecological footprint, showing the total environmental pressure on natural resources of countries, and was obtained from the Global Footprint Network database. The third environmental indicator is the sustainable development score, measuring the level of achievement of sustainable development goals by countries.

Table 1. Data descriptions

Variables	Abbreviation	Measurement	Source
Carbon Emissions	CO	CO_2 Emission (metric tons)	WDI
Ecological Footprint	EF	Total Ecological Footprint (tons)	footprintnetwork.org
Sustainable Development	SD	Sustainable Development Score	Sustainable Development Report
Artificial Intelligence Investments	AII	Number of Artificial Intelligence Investments	OECD
Financial Development	FD	Domestic loans provided to the private sector by banks (% GDP)	WDI
Capital	C	Gross capital formation (% GDP)	WDI
Economic Growth	EG	GDP per capita (constant 2015 US$)	WDI

This data was obtained from the Sustainable Development Report dataset. The main independent variable of the study is artificial intelligence investments, representing the number of artificial intelligence investments made in countries. Data for this variable was obtained from the OECD database. To better analyze the impact of artificial intelligence investments on environmental indicators, some control variables were also icluded in the model. In this context, the financial development variable is measured by the share of domestic loans provided by banks to the private sector in GDP and represents the level at which the financial system supports economic activities. The capital variable is measured by gross capital formation to indicate the total level of investment in the economy.

Finally, the economic growth variable expresses the real per capita income level of countries and is measured as GDP per capita (2010 constant US dollars). By using these variables together, the study aims to obtain more reliable and comprehensive results in analyzing the impact of artificial intelligence investments on environmental quality while also controlling for the effects of macroeconomic factors such as economic growth, financial development, and investment levels.

$$\mathrm{CO}_{i,t} = \beta_0 + \beta_1 \mathrm{AII}_{i,t} + \beta_2 \mathrm{FD}_{i,t} + \beta_3 \mathrm{C}_{i,t} + \beta_4 \mathrm{EG}_{i,t} + \varepsilon_{i,t} \tag{1}$$

$$\mathrm{EF}_{i,t} = \beta_0 + \beta_1 \mathrm{AII}_{i,t} + \beta_2 \mathrm{FD}_{i,t} + \beta_3 \mathrm{C}_{i,t} + \beta_4 \mathrm{EG}_{i,t} + \varepsilon_{i,t} \tag{2}$$

$$\mathrm{SD}_{i,t} = \beta_0 + \beta_1 \mathrm{AII}_{i,t} + \beta_2 \mathrm{FD}_{i,t} + \beta_3 \mathrm{C}_{i,t} + \beta_4 \mathrm{EG}_{i,t} + \varepsilon_{i,t} \tag{3}$$

In this study, three separate econometric models were developed to analyze the impact of artificial intelligence investments on environmental quality. The Model 1 used carbon emissions (CO_2) as the dependent variable, examining the effects of artificial intelligence investments, financial development, capital accumulation, and economic growth on carbon emissions. The Model 2 used ecological footprint as the dependent variable to evaluate environmental sustainability from a different perspective, analyzing the effects of the same explanatory variables on the ecological footprint. The Model 3 considered the sustainable development score, which more comprehensively reflects the environmental and economic sustainability performance of countries, as the dependent variable. The Model 3 also investigated the effects of artificial intelligence investments, financial development, capital, and economic growth on sustainable development. Thus, the aim was to comparatively analyze the effects of artificial intelligence investments on different indicators representing environmental quality through these three developed models.

3.2. Method

In this study, four commonly used tests from the literature were utilized to test cross-sectional dependence (CSD). These included the Breusch-Pagan LM test (1980), Pesaran's scaled LM (CD_{LM}) test (Pesaran et al. 2008), Pesaran's CD test (Pesaran 2004), and the Bias-Corrected Scaled LM (LM_{adj})

test (Pesaran et al. 2008). These tests are used to determine whether error terms are related to each other among the countries in the panel dataset. In other words, these tests aim to reveal whether there are common shocks or mutual interactions among the cross-sectional units in the panel. The four tests used in this study are expressed as Equations (4), (5), (6), and (7), respectively.

$$LM = T\sum_{i=1}^{N-1}\sum_{j=i+1}^{N}\hat{\rho}_{ij}^{\ 2} \tag{4}$$

$$CD_{LM} = \sqrt{\frac{1}{N(N-1)}}\sum_{i=1}^{N-1}\sum_{j=i+1}^{N}\left(T\hat{\rho}_{ij}^{\ 2}-1\right) \tag{5}$$

$$CD = \sqrt{\frac{2T}{N(N-1)}}\left(\sum_{i=1}^{N-1}\sum_{j=1+1}^{N}\hat{\rho}_{ij}\right) \tag{6}$$

$$LM_{adj} = \left(\frac{2}{N(N-1)}\right)^{1/2}\sum_{i=1}^{N-1}\sum_{j=i+1}^{N}\hat{\rho}_{ij}^{2}\frac{(T-K-1)\hat{\rho}_{ij}-\hat{\mu}_{Tij}}{\upsilon_{Tij}} \sim N(0,1) \tag{7}$$

In the second stage, Δ (Delta) slope homogeneity tests developed by Pesaran et al. (2008) were used to determine whether the slope coefficients in the model were homogeneous. These tests were later improved by Blomquist and Westerlund (2013) and expanded to provide more reliable results, especially in panel data analysis. These tests aim to determine whether the slope coefficients are the same among the cross-sectional units in the panel dataset, in other words, whether the model parameters are homogeneous or heterogeneous for all countries. In addition, the robustness of the results was tested by considering the HAC (Heteroskedasticity and Autocorrelation Consistent) version of the Δ test. The equations for the slope homogeneity test used in this context are shown in Equations (8), (9), (10), and (11).

$$\Delta_{HAC} = \sqrt{N}\left(\frac{N^{-1}S_{HAC}-k}{\sqrt{2k}}\right) \tag{8}$$

$$S_{HAC} = \sum_{i=1}^{N}T\left(\hat{\beta}_i-\hat{\beta}\right)'\left(\hat{O}_{iT}V_{iT}^{-1}\hat{O}_{iT}\right)\left(\hat{\beta}_i-\hat{\beta}\right) \tag{9}$$

$$\hat{\beta} = \left(\sum_{i=1}^{N}T\hat{O}_{iT}V_{iT}^{-1}\hat{O}_{iT}\right)^{-1}\sum_{i=1}^{N}\hat{O}_{iT}\hat{V}_{iT}^{-1}X_i'M_T y_i \tag{10}$$

$$\hat{V}_{iT} = \hat{\Gamma}_i(0)+\sum_{j=1}^{T-1}K\left(\frac{j}{M_{iT}}\right)\left[\hat{\Gamma}_i(j)+\hat{\Gamma}_i(j)'\right] \tag{11}$$

In the third stage, the Cross-Sectionally Augmented IPS (CIPS) test, one of the second-generation panel unit root tests, was applied. The CIPS test aims to more reliably test the stationarity properties of series by considering the existence of inter-sectional dependence in panel datasets. Unlike classical unit root tests, this test adds cross-sectional means to the model to control for common shocks and interactions that may occur between countries. In this way, more consistent and reliable results can be obtained in panel data analyses. In this study, the calculations for the CIPS unit root test are shown using Equations (12), (13), (14), (15), and (16).

$$\Delta y_{it} = \alpha_i + \beta_i y_{i,t-1} + u_{it} \tag{12}$$

$$u_{it} = \gamma f_t + \varepsilon_{it} \tag{13}$$

$$\Delta y_{it} = \alpha_i + \rho_i y_{i,t-1} + d_0\bar{y}_{t-1} + d_1\Delta\bar{y}_t + \varepsilon_{it} \tag{14}$$

$$\Delta y_{i,t} = \alpha_i + \rho_i y_{i,t-1} + c_i\bar{y}_{t-1} + \sum_{j=0}^{p}d_{i,j}\,\Delta\bar{y}_{t-j} + \sum_{j=0}^{p}\beta_{i,j}\,\Delta y_{i,t-j} + \mu_{i,t} \tag{15}$$

$$IPS = \frac{1}{N}\sum_{i=1}^{N} CADF_i \tag{16}$$

In the fourth stage, the Panel LM bootstrap cointegration test developed by Westerlund and Edgerton (2007) was used to test for the existence of a long-term relationship between the variables. This test aims to determine whether a long-term equilibrium relationship exists between variables, taking into account cross-sectional dependence in panel data analysis. The use of the bootstrap approach allows for more reliable and consistent results, especially in small samples and in cases where cross-sectional dependence exists. In this context, the model and calculations for the panel cointegration test are shown in Equations (17), (18), and (19).

$$y_{it} = \alpha_i + x'_{it}\beta_i + Z_{it} \tag{17}$$

$$z_{it} = u_{it} + v_{it} \; with \;\; v_{it} = \sum_{j=1}^{t} \eta_{it} \tag{18}$$

$$LM_N^{+} = \frac{1}{NT^2}\sum_{i=1}^{N}\sum_{j=i+1}^{T} \widehat{\omega}_i^{-2}\, S_{it}^2 \tag{19}$$

In the fifth stage, the PCSE (Panel Corrected Standard Errors) estimator, developed by Beck and Katz (1995) and enabling the correction of standard errors, was used to estimate the long-term coefficients. The PCSE method allows for more reliable standard error estimates by considering problems such as heteroskedasticity, autocorrelation, and cross-sectional dependence, which are frequently encountered in panel data analysis. Thanks to this method, the statistical significance of the model coefficients can be evaluated more accurately. The PCSE model and the related estimation equations used in the study are shown in Equations (20), (21), and (22).

$$y_{it} = x_{it}\beta + \varepsilon_{it} \tag{20}$$

$$\begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_m \end{bmatrix} = \begin{bmatrix} X_1 \\ X_2 \\ \vdots \\ X_m \end{bmatrix} \beta + \begin{bmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \vdots \\ \varepsilon_m \end{bmatrix} \tag{21}$$

$$\sum[\varepsilon\varepsilon'] = \Omega = \begin{bmatrix} \sigma_{11}I_{11} & \sigma_{12}I_{12} & \cdots & \sigma_{1m}I_{1m} \\ \sigma_{21}I_{21} & \sigma_{22}I_{22} & \cdots & \sigma_{2m}I_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ \sigma_{m1}I_{m1} & \sigma_{m2}I_{m2} & \cdots & \sigma_{mm}I_{mm} \end{bmatrix} \tag{22}$$

After the PCSE estimation, additional estimations were performed using the Seemingly Unrelated Regressions (SUR) method to validate the long-term coefficients using a second method. According to the Monte Carlo simulation results by Mark et al. (2005), the SUR method provides highly effective and reliable results, especially in cases with high cross-sectional dependence (CSD) and heterogeneity between cross-sections. The SUR method allows estimation by considering the correlation of error terms between different equations. Thus, more efficient and consistent coefficient estimates can be obtained in panel data analyses. The M-equation SUR model and the related estimation equations used in the study are shown in Equations (23), (24), (25), and (26).

$$\begin{aligned} y_1 &= x_1\beta_1 + u_1 \\ y_2 &= x_2\beta_2 + u_2 \\ \vdots \quad & \quad \vdots \qquad \vdots \\ y_M &= x_M\beta_M + u_M \end{aligned} \tag{23}$$

$$\begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_M \end{bmatrix} = \begin{bmatrix} X_1 & 0 & \dots & 0 \\ 0 & X_2 & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & X_M \end{bmatrix} + \begin{bmatrix} \beta_1 \\ \beta_2 \\ \vdots \\ \beta_M \end{bmatrix} + \begin{bmatrix} u_1 \\ u_2 \\ \vdots \\ u_M \end{bmatrix} \tag{24}$$

$$\Sigma = \begin{bmatrix} \sigma_{11} & \sigma_{12} & \dots & \sigma_{1M} \\ \sigma_{21} & \sigma_{22} & \dots & \sigma_{2M} \\ \vdots & \vdots & \ddots & \vdots \\ \sigma_{M1} & \sigma_{M2} & \dots & \sigma_{MM} \end{bmatrix} \tag{25}$$

$$\hat{\beta} = [x'\Omega^{-1}x]^{-1}x'\Omega^{-1}y = [x'(\Sigma^{-1} \otimes I)x]^{-1}x'(\Sigma^{-1} \otimes I)y \tag{26}$$

In order to test the consistency and robustness of the model results obtained with the SUR estimator, the PCSE and Driscoll-Kraay estimators, developed as alternatives to this method, were also used in the study. The Driscoll-Kraay method provides more reliable standard error estimates by considering the problems of heteroskedasticity, autocorrelation, and cross-sectional dependence frequently encountered in panel data analysis. Therefore, the robustness and reliability of the model findings were evaluated by comparing the results obtained from different estimation methods.

In the sixth stage, the panel causality test developed by Dumitrescu and Hurlin (2012) was applied to examine the causal relationships between the variables. This test is a suitable method, especially for heterogeneous panel data structures and cases where cross-sectional dependence (CSD) is present. The Dumitrescu-Hurlin causality test allows for the revelation of short-term dynamic interactions by analyzing the causal relationship between variables X and Y among the cross-sectional units in the panel. The Dumitrescu-Hurlin panel bootstrap causality test is shown in Equation (27):

$$y_{i,t} = \alpha_i + \sum_{k=1}^{K} \beta_{ik}\, y_{i,t-k} + \sum_{k=1}^{K} \gamma_{i,k}\, X_{i,t-k} + \varepsilon_{it} \tag{27}$$

4. Findings

4.1. Descriptive statistics and correlation matrix

This section of the research will cover descriptive statistics and correlation analysis in terms of the dependent and independent variables used in the study.

Table 2. Descriptive statistics

Variable(s)	Obs	Mean	Std.dev	Min	Max
CO	228	16.36	1.39	10.20	18.32
EF	228	4.75	1.58	0.43	8.49
SD	228	76.87	6.48	56.30	86.40
AII	228	195.24	409.64	1.00	2602.00
FD	228	100.43	39.70	25.43	194.67
C	228	24.47	6.69	14.63	53.71
EG	228	10.20	0.91	7.20	11.51

Table 2 presents descriptive statistics for all 228 observations. Environmental indicators show a relatively limited distribution across countries: carbon emissions average 16.36 (std. dev. 1.39), ecological footprint 4.75 (std. dev. 1.58), and sustainable development score 76.87 indicating generally high sustainability performance among the selected countries. The main explanatory variable, AI investments, displays a highly heterogeneous distribution with a mean of 195.24 but a standard deviation of 409.64 and values ranging from 1 to 2602. Control variables similarly vary widely, particularly financial development (mean 100.43, range 25.43-194.67), while capital (mean 24.47) and economic growth (mean 10.20) show more moderate dispersion.

Table 3. Number of artificial intelligence investments by country

Countries	Mean	Std.dev	Min	Max
Australia	57	40.58	2	122
Brazil	34.42	28.03	4	85
China	858.58	520.76	54	1685
Denmark	13.42	8.73	2	27
Finland	18.83	7.7	9	30
France	107.75	67.87	17	194
Germany	94.17	69.99	12	195
India	177.92	132.15	21	412
Ireland	17.42	11.12	2	33
Japan	192.17	142.99	10	416
Korea	228.83	222.21	6	603
Malaysia	9.17	7.58	1	21
Poland	8.33	6.96	1	20
Spain	44.42	33.94	8	108
Sweden	26.83	19.08	1	52
United Kingdom	220.92	131.3	29	392
United States	1480.67	660.17	417	2602
Israel	102.08	59.6	16	193
Italy	16.67	10.9	2	32

Table 3 confirms a highly heterogeneous distribution of AI investments across countries. The United States leads by a wide margin (mean: 1480.67, range: 417-2602), followed by China (858.58), South Korea (228.83), the United Kingdom (220.92), Japan (192.17), and India (177.92). European countries show moderate investment levels, with France (107.75) and Germany (94.17) at the higher end, while Poland (8.33), Malaysia (9.17), Denmark (13.42), and Italy (16.67) record the lowest averages. Overall, AI investments are heavily concentrated in large economies, with high standard deviations across most countries reflecting both significant cross-country differences and temporal fluctuations tied to technological capacity, R&D expenditure, and digital transformation policies.

Table 4. Correlation matrix

	CO	EF	SD	AII	FD	C	EG
CO	1						
EF	0.0774	1					
SD	0.0631	0.5059	1				
AII	0.0106	0.2085	-0.2141	1			
FD	0.0361	0.2269	0.2107	-0.0006	1		
C	-0.1975	-0.2298	-0.4406	0.2406	0.2056	1	
EG	0.1157	0.7731	0.7668	0.0389	0.182	-0.3175	1

Table 4 reveals that carbon emissions show generally weak correlations with all variables, including AI investments (0.0106), ecological footprint (0.0774), and economic growth (0.1157). The ecological footprint displays stronger associations, most notably with economic growth (0.7731) and financial development (0.2269), while showing a moderate negative correlation with capital (-0.2298). The sustainable development score similarly correlates strongly with economic growth (0.7668) and positively with financial development (0.2107), but negatively with AI investments (-0.2141) and capital (-0.4406). Overall, the absence of high inter-variable correlations suggests that multicollinearity is unlikely to pose a significant problem in the econometric analyses.

4.2. Cross-sectional dependence, unit root, and homogeneity test results

This section presents the results of cross-sectional dependence, unit root, and slope homogeneity tests for the variables used in the study.

Table 5. Cross-sectional dependence test results

Variables	**CO**	**EF**	**SD**	**AII**	**FD**	**C**	**EG**
Breush-Pagan LM	342.65***	344.53***	364.12***	286.64***	175.75***	355.76***	374.64***
Pesaran scaled LM	76.12***	42.54***	67.12***	58.19***	89.23***	39.27***	84.21***
Bias-corrected scaled LM	43.12***	36.12***	36.74***	35.19***	21.08***	39.13***	18.93***
Pesaran CD	12.75***	15.86***	8.95***	12.85***	11.72***	19.18***	19.87***

Table 5 presents the results of the cross-sectional dependence (CSD) tests applied to the variables in the panel dataset. Cross-sectional dependence can occur in panel data analyses when there are common shocks or mutual interactions between countries. Therefore, the cross-sectional dependence between variables was investigated using Breusch-Pagan LM, Pesaran scaled LM, Bias-corrected scaled LM, and Pesaran CD tests. Examining the results, it is seen that the test statistics are statistically significant at the 1% level for all variables. In particular, according to the Breusch-Pagan LM test results, high test statistics were obtained for all variables: CO, EF, SD, AII, FD, C, and EG. Similarly, the Pesaran scaled LM, Bias-corrected scaled LM, and Pesaran CD tests also yielded significant results for all variables. These findings indicate a strong cross-sectional dependence among the countries in the panel dataset.

In other words, it is understood that the economic and environmental indicators of the countries included in the analysis are not independent of each other and can be affected by common factors such as global economic developments, technological changes, fluctuations in energy markets, or international policies. The fact that macroeconomic variables such as artificial intelligence investments, financial development, and economic growth have dynamics that can influence each other on a global scale supports this result. Therefore, these results show that second-generation panel data methods, which take cross-sectional dependence into account, should be used in panel data analysis. For this reason, in the subsequent stages of the study, second-generation panel unit root and cointegration tests were applied to ensure more reliable results.

Table 6. Slope homogeneity test

	Model 1	Model 2	Model 3
$\tilde{\Delta}$	13.74***	9.86***	12.86***
$\tilde{\Delta}_{adj}$	8.32***	9.65***	8.65***

Table 6 presents the results of the slope homogeneity test for the three models established in this study. In panel data analysis, the slope homogeneity test is applied to determine whether the coefficients in the model are the same for all cross-sectional units (countries). In this study, the Δ (Delta) and corrected Δadj test statistics developed by Blomquist and Westerlund (2013) were used to test slope homogeneity.

Examining the results, it is seen that both the Δ and Δadj test statistics are statistically significant at the 1% significance level for all models. This indicates that the null hypothesis of the test, slope homogeneity (H_0: the coefficients are the same for all countries), is rejected. In other words, it is understood that the slope coefficients are not the same among countries for Model 1, Model 2, and Model 3 established in this study, and that slope heterogeneity exists.

This result shows that the countries in the panel have different characteristics in terms of economic structure, technology investments, financial development level, and environmental policies. Therefore, it is understood that the impacts of artificial intelligence investments on carbon emissions, ecological footprint, and sustainable development may differ between countries. For this reason, it is of great importance that the econometric methods used in the analysis process are methods that take into account the heterogeneous panel data structure.

Table 7. CIPS unit root test results

Variables	CIPS test statistics - constant	
	Level	First Difference
CO	-1.38	-4.21***
EF	-1.85	-4.96***
SD	-1.27	-5.86***
AII	-1.96*	-4.21***
FD	-1.19	-6.84***
C	-1.18	-5.12***
EG	-1.04*	-4.86***
CO	-0.59	-4.75***

Table 7 presents the results of the CIPS (Cross-Sectionally Augmented IPS) panel unit root test applied to determine the stationarity properties of the variables. The CIPS test is a second-generation unit root test that takes into account cross-sectional dependence between countries in panel datasets and allows for a more reliable determination of whether the series are stationary.

Examining the test results, it is seen that the vast majority of variables are not stationary at the level values. In particular, the CIPS test statistics for variables CO, EF, SD, FD, and C remain above the critical values at the level values, indicating that the series contain a unit root at the level. While there is limited significance at the level values for variables AII and EG, it can be said that the variables are generally not stationary at the level.

In contrast, when the first differences of all variables are taken, the CIPS test statistics are statistically significant at the 1% significance level. This result shows that the first differences of the variables are stationary and that the series are integrated at the I(1) level. These findings indicate that while the variables used in the analysis are not stationary at the level, they become stationary in their first differences. This suggests that cointegration analysis can be applied to test the existence of a long-term relationship between the variables.

4.3. Long-term coefficient and causality tests

In this section, long-term coefficients and causality relationships are estimated.

Table 8. Westerlund-Edgerton's LM bootstrap cointegration test

Models	Test	LM Statistics	Asymptotic-p	Boostrap-p
Model 1	LMN^T	15.97	0.0000	0.895
Model 2	LMN^T	17.24	0.0000	0.827
Model 3	LMN^T	13.67	0.0000	0.832

Table 8 presents the results of the Westerlund and Edgerton (2007) LM Bootstrap cointegration test, applied to determine the existence of a long-term relationship between the variables. The null hypothesis of this test is H_0: there is cointegration between the variables. Bootstrap p-values are considered in interpretations, especially in panel datasets with cross-sectional dependence, as they provide more reliable results.

Table 8 shows that the bootstrap p-values obtained for Model 1, Model 2, and Model 3 are 0.895, 0.827, and 0.832, respectively. Since all these values are greater than the 0.05 significance level, the null hypothesis of the test cannot be rejected. In other words, it is concluded that there is a long-term cointegration relationship between the variables in the models. This result indicates the existence of a long-term equilibrium relationship between AI investments, financial development, capital, and economic growth variables, and carbon emissions, ecological footprint, and sustainable development score, which represent environmental quality. Therefore, it can be said that despite short-term fluctuations of the variables, they move together in the long term. The identification of a cointegration relationship suggests that using panel estimation methods for estimating long-term coefficients in the next stage of the study is appropriate.

Table 9. The impact of artificial intelligence investments on carbon emissions

	Model 1		
Method	**PCSE**	**SUR**	**D-K**
Dependent Variable	CO	CO	CO
AII	2.21** (0.02)	1.95** (0.03)	1.98** (0.02)
FD	2.45* (0.18)	2.02* (0.24)	2.15** (0.19)
C	-1.58* (0.16)	-2.42** (0.45)	-2.08* (0.19)
EG	5.89*** (1.07)	6.64*** (1.75)	5.87*** (1.21)
Fixed	5.45*** (1.11)	6.03*** (1.32)	6.15*** (1.07)
Number of Observations	228	228	228
R^2	0.2514	0.2871	0.2682
Number of Groups	19	19	19

Table 9 presents long-term coefficient estimates from PCSE, SUR, and Driscoll-Kraay methods for the carbon emissions model, with results remaining consistent across all three techniques confirming methodological robustness.

AI investments show a positive and statistically significant effect on carbon emissions across all models (PCSE: 2.21, SUR: 1.95, D-K: 1.98), indicating that the expansion of AI technologies through high energy consumption, data center growth, and digital infrastructure investment contributes to increased carbon emissions. Among control variables, financial development exerts a positive and significant effect, reflecting how expanded economic activity raises emissions. Capital accumulation, by contrast, shows a negative and significant coefficient across all models, suggesting that investment in more efficient production technologies can reduce carbon pressure. Economic growth displays the strongest positive effect, with high coefficients confirming that increased production and energy consumption levels drive carbon emissions upward.

Table 10. The impact of artificial intelligence investments on ecological footprint

	Model 2		
Method	**PCSE**	**SUR**	**D-K**
Dependent Variable	EF	EF	EF
AII	4.53*** (0.07)	5.21*** (0.13)	4.85*** (0.09)
FD	5.39*** (0.12)	4.54*** (0.14)	4.85*** (0.27)
C	-2.52*** (0.16)	-1.99*** (0.14)	-2.45*** (0.22)
EG	10.47*** (1.24)	14.68*** (1.32)	132.54*** (1.27)
Fixed	14.58*** (2.85)	12.11*** (2.78)	8.47*** (1.13)
Number of Observations	228	228	228
R^2	0.6413	0.6185	0.6352
Number of Groups	19	19	19

Table 10 presents ecological footprint estimation results from PCSE, SUR, and Driscoll-Kraay methods, with coefficients consistent in direction and significance across all three confirming robustness.

AI investments show a positive and statistically significant effect at the 1% level across all models (PCSE: 4.53, SUR: 5.21, D-K: 4.85), indicating that AI expansion increases ecological footprint through higher energy consumption, data center growth, and rising natural resource use. Among control variables, financial development exerts a positive and significant effect, reflecting how expanded economic activity amplifies pressure on natural resources. Capital accumulation again shows a negative and significant coefficient, suggesting efficiency gains from investment reduce environmental pressure. Economic growth displays a strong positive effect, as increased production and consumption activities intensify natural resource use. The model explains approximately 62-64% of the variation in ecological footprint, indicating satisfactory explanatory power.

Table 11. The impact of artificial intelligence investments on sustainable development scores

	Model 3		
Method	**PCSE**	**SUR**	**D-K**
Dependent Variable	SD	SD	SD
AII	-5.84^{***} (-0.03)	-5.78^{***} (-0.04)	-6.05^{***} (-0.05)
FD	10.79^{***} (0.02)	11.58^{***} (0.04)	11.04^{***} (0.04)
C	-9.83^{***} (-0.19)	-10.18^{***} (-0.22)	-9.28^{***} (-0.14)
EG	10.84^{***} (1.89)	9.79^{***} (1.75)	11.07^{***} (1.46)
Fixed	20.02^{***} (5.45)	18.48^{***} (5.21)	17.48^{***} (4.14)
Number of Observation	228	228	228
R^2	0.6838	0.6752	0.6807
Number of Groups	19	19	19

Table 11 presents sustainable development score estimation results from PCSE, SUR, and Driscoll-Kraay methods, with coefficients consistent in direction and significance across all three confirming robustness.

AI investments show a negative and statistically significant effect at the 1% level across all models (PCSE: -5.84, SUR: -5.78, D-K: -6.05). Given that the sustainable development score is a multidimensional indicator encompassing environmental, social, and economic dimensions, this result suggests that AI's short-term environmental pressures through energy consumption and digital infrastructure expansion create a limiting effect on overall sustainability performance. Among control variables, financial development exerts a positive and significant effect, supporting sustainable development performance. Capital accumulation shows a negative and significant coefficient, potentially reflecting resource-intensive investment patterns in some countries. Economic growth displays a strong positive effect across all models. However, the possibility of endogeneity should be noted: countries with higher sustainable development performance may also invest more in AI, raising reverse causality concerns. The findings therefore reveal a statistical relationship between variables rather than a definitive causal effect.

Table 12 presents Dumitrescu-Hurlin panel causality results. Across all three environmental indicators, a consistent pattern emerges: unidirectional causality runs from AI investments to carbon emissions ($p=0.048$), ecological footprint ($p=0.000$), and sustainable development score ($p=0.000$), with no reverse causality detected in any case. Financial development and capital similarly exhibit unidirectional causality toward all three environmental indicators. Economic growth, by contrast, displays a bidirectional relationship with all environmental indicators ($p<0.01$), reflecting a dynamic mutual interaction between growth and environmental performance. Overall, these findings confirm that AI investments systematically precede and shape environmental outcomes, while the relationship between economic growth and environmental quality operates in both directions.

Table 12. Dumitrescu-Hurlin panel causality test results

	W-bar	Z-bar	P-values
CO ↛ AII	1.041	0.527	0.475
AII ↛ CO	2.428	2.014	0.048
CO ↛ FD	0.874	0.548	0.695
FD ↛ CO	3.428	4.108	0.000
CO ↛ C	0.569	1.019	0.528
C ↛ CO	2.138	2.428	0.039
CO ↛ EG	2.952	3.172	0.001
EG ↛ CO	3.425	4.595	0.000
EF ↛ AII	0.751	0.435	0.652
AII ↛ EF	3.577	4.192	0.000
EF ↛ FD	0.752	0.419	0.719
FD ↛ EF	3.951	5.295	0.000
EF ↛ C	0.385	0.546	0.807
C ↛ EF	2.295	2.819	0.004
EF ↛ EG	3.158	5.095	0.000
EG ↛ EF	4.052	6.019	0.000
SD ↛ AII	0.935	0.875	0.395
AII ↛ SD	2.856	3.284	0.000
SD ↛ FD	1.047	1.238	0.153
FD ↛ SD	3.297	4.598	0.000
SD ↛ C	0.695	0.728	0.459
C ↛ SD	2.218	2.435	0.043
SD ↛ EG	3.286	5.421	0.000
EG ↛ SD	4.219	6.838	0.000

Note: The maximum delay length is set to 1.

5. Discussion

The most notable finding of this study is that artificial intelligence (AI) investments significantly increase carbon emissions. This finding indicates that the widely accepted view that AI is a technology that automatically promotes environmental sustainability does not hold universally across all countries and time periods. The literature contains numerous studies suggesting that AI can reduce carbon emissions by improving energy efficiency. In particular, Zhao et al. (2024), Dong et al. (2024), Cao et al. (2025), Chen et al. (2026), and Zhou et al. (2024) demonstrate that AI can reduce emissions by optimizing production processes, enhancing smart energy management, and accelerating the adoption of green technologies. However, a substantial proportion of these studies primarily emphasize the efficiency gains generated by AI while giving relatively limited attention to the additional energy demand created by these technologies. In recent years, the scale of AI investments has expanded far beyond software development alone and has increasingly involved the rapid proliferation of large-scale data centers, cloud computing infrastructure, high-performance processors, and continuously operating digital networks, all of which have substantially increased electricity consumption. Particularly in economies where electricity generation still relies heavily on fossil fuels, the energy efficiency gains provided by AI may not be sufficient to offset the resulting increase in carbon emissions in the short run. From this perspective, the present findings support the arguments advanced by Xu and Song (2023), Luo and Feng (2024), Zhou et al. (2026), and Abd El-Aal (2025), who suggest that the environmental effects of AI are not linear but rather depend on countries' energy production structures and institutional characteristics. Therefore, the environmental consequences of AI investments should not be evaluated solely from a technology-oriented perspective but should instead be considered together with energy transition policies, electricity generation sources, and environmental regulations.

The literature on ecological footprints likewise presents no clear consensus. Rahman et al. (2026) report that the joint development of energy innovation and AI investments reduces ecological footprints in G7 countries, while Balcı et al. (2026) show that AI can strengthen environmental sustainability when supported by educational investments and human capital development. In contrast, Balsalobre-Lorente et al. (2026) argue that the environmental impact of AI depends largely on energy policies and environmental governance mechanisms and that technological development may increase ecological pressures in the absence of an appropriate institutional framework. The findings of the present study are more consistent with the latter perspective. Although the countries included in the analysis are among the global leaders in AI investments, the transition toward cleaner energy systems does not appear to have progressed at the same pace as technological advancement. In other words, the contribution of AI investments to environmental sustainability depends not only on technological capacity but also on the expansion of renewable energy, improvements in the energy efficiency of data centers, and the development of low-carbon digital infrastructure. This interpretation is also consistent with the increasingly influential concept of Green Artificial Intelligence. As emphasized by Bolón-Canedo et al. (2024), achieving sustainable environmental outcomes requires not only the application of AI to solve environmental problems but also the development of AI technologies that consume less energy and generate lower carbon footprints throughout their entire life cycle. Accordingly, the findings of this study indicate that AI should not be regarded as a standalone solution for environmental sustainability but rather as a strategic technology whose environmental benefits depend on its integration with energy, industrial, and environmental policies.

Another important finding of this study is that AI investments have a statistically significant negative effect on sustainable development scores. This result demonstrates that the environmental implications of AI extend beyond carbon emissions and natural resource use and should be evaluated within the broader context of sustainable development, which encompasses environmental, economic, and social dimensions simultaneously. Sustainable development scores incorporate a wide range of indicators, including access to clean energy, responsible production and consumption, climate action, institutional quality, social welfare, and economic development. Consequently, the substantial energy demand created by AI investments, the resource-intensive nature of digital infrastructure, and the rapidly increasing electricity consumption of data centers may outweigh the long-term efficiency gains expected from technological progress. Particularly in economies where AI investments have not yet been fully integrated with the energy transition, it is reasonable that technological advancement may fail to generate the anticipated improvements in sustainable development performance. Therefore, the findings suggest that the contribution of AI to sustainable development is neither automatic nor linear but depends fundamentally on the existence of complementary environmental and energy policies.

This finding differs from several empirical studies reporting that AI promotes sustainable development. Spagnuolo et al. (2025) conclude that AI applications strengthen sustainable development performance among European state-owned enterprises, while Varriale et al. (2026) identify AI as a major catalyst for achieving the Sustainable Development Goals through technological networks. Likewise, Fazal et al. (2025) demonstrate that AI supports sustainable development through financial inclusion, whereas Apata et al. (2025) and Jogezai et al. (2026) argue that AI contributes substantially to sustainable development objectives, particularly in the field of education. However, most of these studies focus either on specific sectors or on individual Sustainable Development Goals rather than examining the macro-level impact of AI on countries' overall sustainable development performance. Furthermore, AI is frequently analyzed together with complementary variables such as energy transition and institutional quality, making it difficult to isolate its independent effect. In contrast, the negative association identified in this study suggests that technological progress alone is insufficient to enhance sustainable development performance and that decarbonizing energy systems, strengthening environmental governance, and simultaneously promoting sustainable production models are essential prerequisites for realizing the environmental and social benefits of AI.

Taken together, the findings reveal that the environmental effects of AI investments are highly complex and multidimensional. AI is frequently portrayed in the literature as a technology capable of improving energy efficiency, optimizing resource utilization, and accelerating the green transition. However, the present findings indicate that the environmental benefits of technological progress may not materialize immediately and that, particularly in economies experiencing rapid expansion of AI investments, the growing energy demand associated with digital infrastructure may generate substantial environmental costs. This interpretation is consistent with the nonlinear relationship proposed by Wang et al. (2026) and Melguizo et al. (2026), who argue that the environmental consequences of AI depend on countries' energy mix, financial development, institutional capacity, and the effectiveness of environmental policies. Accordingly, AI investments should not be regarded as a direct driver of environmental sustainability but rather as a complementary technology capable of generating environmental benefits only when supported by appropriate institutional arrangements and coherent energy policies.

6. Policy implications and practical insights

The findings of this study suggest that technological advancement alone is insufficient for artificial intelligence (AI) investments to contribute to environmental sustainability and that energy, industrial, and environmental policies must be implemented in a coordinated manner. Although AI applications are expanding rapidly, the simultaneous increase in carbon emissions and ecological footprints indicates that digital transformation is not progressing at the same pace as the energy transition. Therefore, while encouraging AI investments, policymakers should prioritize regulations requiring data centers, cloud computing infrastructure, and high-performance computing systems to operate using renewable energy sources. In particular, the environmental costs of AI infrastructure can be reduced by introducing green energy obligations, energy efficiency standards, and carbon reporting systems for large-scale data centers. The findings also demonstrate that AI investments increase pressure on natural resource utilization. This indicates that digital transformation policies should not focus solely on software development and algorithmic innovation. The recovery of critical minerals used in hardware production, the effective recycling of electronic waste, and the widespread implementation of circular economy practices should become integral components of the AI ecosystem. Furthermore, public support mechanisms should be differentiated not only according to the scale of AI investments but also according to technologies that develop energy-efficient algorithms and minimize environmental impacts. In this way, investment incentives can be transformed into a system that rewards not only technological growth but also environmental performance.

The findings regarding sustainable development scores indicate that although AI investments support economic growth, they do not generate the same level of success in the environmental and social dimensions of sustainable development. Therefore, Sustainable Development Goals should become an integral component of national AI strategies. The evaluation of AI investments should not rely solely on indicators such as investment volume, patent output, or economic value added, but should also incorporate performance criteria related to carbon intensity, energy efficiency, natural resource consumption, and contributions to sustainable development performance. Such an approach would facilitate the integration of technology-driven growth strategies with the broader objectives of sustainable development.

Finally, the study demonstrates that the environmental effects of AI cannot be evaluated independently of countries' energy production structures and institutional capacities. Consequently, AI policies should be designed in conjunction with renewable energy investments, smart electricity grids, carbon pricing mechanisms, environmental regulations, and green finance initiatives in order to ensure environmental sustainability. In particular, the wider adoption of AI-enabled energy management systems across industry, transportation, and public services would not only accelerate digital transformation but also contribute to optimizing energy consumption and reducing carbon emissions. In this way, AI can be transformed from a technology that increases environmental pressures into a strategic instrument that supports sustainable development.

7. Limitations and directions for future research

This study has several limitations, which also provide important opportunities for future research. First, the analysis is limited to the 19 countries with the highest levels of artificial intelligence investments and the 2012-2023 period. Therefore, the findings cannot be directly generalized to countries with different income levels or less developed artificial intelligence ecosystems. In addition, because the analysis covers a relatively short period during which artificial intelligence technologies have expanded rapidly, it is not possible to fully capture the long-term environmental effects of these technologies. Furthermore, artificial intelligence investments are represented by a single indicator, and no distinction is made between generative artificial intelligence, industrial artificial intelligence, robotics applications, or sector-specific artificial intelligence investments. Accordingly, it should be recognized that the environmental impacts of different types of artificial intelligence may vary considerably.

Moreover, environmental sustainability is evaluated using carbon emissions, ecological footprint, and sustainable development scores, while alternative environmental indicators such as biocapacity, green total factor productivity, environmental performance index, carbon neutrality, and circular economy indicators are not incorporated into the analysis. Similarly, complementary factors that may shape the environmental effects of artificial intelligence investments, including the effectiveness of environmental regulations, energy transition policies, green finance, institutional quality, digital governance, environmental innovation, and renewable energy infrastructure, are not considered within the proposed model. Consequently, the findings reflect the direct effects of artificial intelligence investments on environmental quality but do not capture potential mediating or moderating mechanisms.

Future studies should include a broader set of countries and longer time horizons in order to improve the external validity of the findings. Furthermore, studies that separately examine different types of artificial intelligence investments, consider nonlinear relationships, and investigate the mediating or moderating roles of variables such as green finance, environmental policy management, institutional quality, energy transition, digitalization, and environmental innovation would make important contributions to the literature. In addition, employing panel quantile regression, threshold models, nonlinear panel estimation techniques, and artificial intelligence-based forecasting approaches would provide a more comprehensive understanding of the heterogeneous effects of artificial intelligence investments on environmental sustainability and further advance the existing body of knowledge.

Declaration of competing interest

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

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Shaping sustainable futures: The roles of green innovation, green growth, and energy efficiency in trade-adjusted carbon emissions

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ABSTRACT

This study examines the long-run effects of green growth, green innovation, energy efficiency, and industrialisation on trade-adjusted carbon emissions using panel data from the world's 15 most innovative countries over 2003-2023. Second-generation panel techniques address cross-sectional dependence and slope heterogeneity, with cointegration confirmed via Westerlund's ECM-based tests. SUR, PCSE, and Driscoll-Kraay estimators consistently demonstrate that green growth, green innovation, and energy efficiency significantly reduce emissions, while industrialisation significantly increases them. Dumitrescu-Hurlin causality tests confirm unidirectional causality from the former three to emissions and a bidirectional relationship with industrialisation. Renewable energy expansion, clean technology investment, and energy productivity improvements are effective levers for reducing trade-related carbon emissions. Industrialisation, however, continues to carry a substantial carbon cost even in technologically advanced economies. Governments should integrate carbon pricing and emission standards into industrial policy, while innovation agencies should channel R&D funding toward clean technologies through green procurement and targeted incentive schemes.

1. Introduction

Green growth is an approach to development that aims to balance economic development and environmental sustainability (Radulescu et al. 2025; Yazıcı and Çiçelioğlu 2025). According to this theory, economic growth should be possible not only through increased production, but also through the efficient use of natural resources, the development of environmentally friendly technologies and the reduction of environmental damage (Abid et al. 2022). Green growth is seen as a key strategy for achieving sustainable development goals and supports holistic development in areas such as energy consumption, environmental quality, health and welfare (Zaman et al. 2016). In this context, the implementation of environmental management systems such as ISO 14001 and the dissemination of technological innovations are important tools that strengthen the green growth process. In order to achieve sustainable development goals, green economy policies need to be strengthened and integrated into energy, industry and trade (Adamowicz 2022; Alrasheedi et al. 2021). Research in emerging economies such as BRICS and Africa shows that the transition to clean energy and environmentally friendly production processes both provide environmental protection and support long-term economic

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growth (Gu et al. 2018). Therefore, green growth is becoming one of the fundamental building blocks of sustainable development by not only reducing environmental threats but also creating new economic opportunities.

One of the main pillars of green growth is to reduce environmental damage through technological transformation and innovation. At this point, green innovation stands out as both a carrier and a complement to the green growth strategy and creates decisive effects on environmental quality. Green innovation is an important strategy that has the potential to reduce the conflict between economic growth and environmental sustainability (Ali et al. 2022; Wen et al. 2021). This approach makes it possible to systematically reduce carbon emissions by encouraging the development and diffusion of technologies that minimise environmental impacts (Liu et al. 2022; Zhao et al. 2025). The environmental benefits of green innovation stem not only from the transformation of production processes but also from multifaceted practices such as energy efficiency, waste management and environmentally friendly product design (Afshan and Yaqoob 2023; Khurshid et al. 2023). Moreover, this form of innovation is also considered as a structural transformation tool that enables firms to generate economic value without harming the environment by facilitating compliance with environmental regulations (Meng et al. 2022; Zhao et al. 2024).

The impact of green innovation in reducing environmental pollution covers not only carbon emissions but also broader environmental indicators such as ecological footprint (Ke et al. 2022; Koseoglu et al. 2022). Its positive impact on ecological footprint is associated with increasing efficiency in resource use and reducing harmful outputs left to nature (Zhang and Yasin 2024; Wei et al. 2023). Moreover, it has been stated that digital infrastructures and renewable energy investments are important complements in increasing the effectiveness of green innovation (Zhao et al. 2024). On the other hand, the success of these innovations is largely supported by regulatory elements such as environmental taxes, carbon pricing and policy stability (Khurshid et al. 2023). As a result, green innovation is at the centre of strategies to reduce environmental pollution by providing not only a technological but also an institutional and governance framework to prevent environmental degradation (Afshan and Yaqoob 2023; Liu et al. 2022).

While the positive effects of green growth and green innovation on environmental quality form the basis of sustainable development approaches, the successful implementation of this process largely depends on the transformation of energy systems. In this context, energy efficiency, and especially the share of renewable energy supply in total energy, stands out as an important factor that plays a decisive role on the environment. In order for the low-carbon economic structures required by green growth and the environmentally friendly technologies offered by green innovation to be effective, the orientation towards renewable resources in energy production should be strengthened. Wahab et al. (2021) and Ahmad et al. (2022) state that increasing the share of renewable energy limits carbon emissions and prevents environmental degradation. Likewise, Kirikkaleli and Ali (2024) and Ge and Mehmood (2024) emphasise that an increase in renewable energy supply directly improves environmental quality. Accordingly, increased use of renewable energy not only reduces carbon emissions, but also contributes to shrinking the ecological footprint, reducing air pollution and maintaining environmental carrying capacity (Ke et al. 2022; Addai et al. 2022). On the contrary, a low or decreasing share of renewable energy threatens environmental sustainability and contradicts green growth goals by maintaining fossil fuel dependence (Liu et al. 2023; Kirikkaleli et al. 2023a). Studies such as Safi et al. (2023) highlight the significant role of the renewable energy share in improving environmental performance and demonstrate that it is a strategically important indicator for policymakers. Therefore, to maximize the environmental benefits of green growth and green innovation, increasing the share of renewable energy in the overall energy supply should be considered an integral component of environmental and sustainable development policies.

While energy efficiency has been shown to be an important factor supporting environmental sustainability, industrialisation stands out as a factor that is opposite to this dynamic and has the potential to increase environmental pressures. While industrialisation provides positive contributions in terms of economic development and employment creation, it can become a threat to environmental quality by increasing fossil fuel consumption, especially in traditional production structures (Opoku and Aluko 2021; Elfaki et al. 2022). The increase in energy demand with the expansion of industrial activities brings environmental problems such as carbon emissions, air pollution and natural resource consumption. The lack of environmentally sensitive technologies and weak environmental regulations in developing countries further exacerbate these negative impacts (Musah and Yakubu 2022; Rehman et al. 2021).

However, the environmental impacts of industrialisation are not one-dimensional; the effectiveness of the environmental policies implemented, the structure of the industrial sector and the energy resources used can determine the direction of this relationship. For example, increasing environmental policy stringency can reduce the negative impacts of industrialisation on the environment (Nkemgha et al. 2024). Moreover, it is possible to restructure industrial production in a way that is less damaging to the environment through the diffusion of low-carbon technologies and the integration of renewable energy. However, it is noted that industrialisation is not only limited to carbon emissions, but also has an impact on broader environmental pressure indicators such as ecological footprint, which may conflict with sustainable development goals (Quito et al. 2023; Li and Zhang 2023). Therefore, the environmental impacts of industrialisation should be assessed together with the production structure, technological capacity and policy framework.

In a period when global environmental problems are deepening, the importance of environmentally friendly policies and structural transformations is increasing in order to achieve sustainable development goals. In particular, countries with high technological development are expected to assume a more responsible and guiding role in terms of sustainability. In this context, increasing the use of renewable energy, encouraging green innovation, using resources more efficiently and making industrial production compatible with the environment are among the basic strategies for protecting environmental quality. In order to evaluate the effectiveness of these strategies, this study aims to examine the effects of green growth, green innovation, energy efficiency and industrialization on trade-adjusted carbon emissions using annual data from the world's 15 most innovative countries for the period 2003-2023. The findings obtained using SUR, PCSE and Driscoll-Kraay methods within the scope of dynamic panel data analysis offer important implications for the management of sustainability policies.

This study is expected to make several important contributions to the existing literature. It examines the effects of four key variables, namely green growth, green innovation, energy efficiency, and industrialization, on trade-adjusted carbon emissions (*TAEM*) within a unified empirical framework, thereby providing a more holistic perspective on the determinants of environmental sustainability. Unlike previous studies that primarily focus on individual factors, this research evaluates the combined environmental effects of these variables within a single model. Furthermore, by focusing on the 15 most innovative countries in the world, the study assesses the environmental sustainability performance of economies that are global leaders in technological development and innovation. As these countries are generally at the forefront of technology production, they serve as valuable benchmarks for the implementation of environmentally sustainable policies. Accordingly, the study offers an original assessment of the environmental responsibilities of advanced and innovation driven economies.

Another important contribution of the study is the use of trade-adjusted carbon emissions (*TAEM*) as the environmental indicator. Unlike conventional production-based carbon emission measures, *TAEM* incorporates carbon leakage and emissions embodied in international trade, thereby providing a more comprehensive and realistic assessment of environmental impacts. This approach also enhances the relevance of the study's findings for contemporary environmental policymaking. Finally, the empirical findings provide a basis for developing concrete policy recommendations on how environmental, energy, and industrial policies can be designed to promote sustainability. The results are expected to serve as a useful reference for policymakers, particularly in the formulation of strategies aimed at reducing carbon emissions. In this respect, the study offers valuable implications for public authorities, local governments, and international organizations committed to achieving sustainable environmental outcomes.

This study consists of five sections. The first section is the introduction, followed by a summary of the literature on the relationship between *GG, GIN, EP, IND* and *TAEM*. The third section describes the dataset and method used in the study in detail. The fourth section presents empirical findings and compares the results with previous studies. The final section provides both theoretical and practical implications and provides policy recommendations.

2. Literature review

2.1. The relationship between green growth and environmental quality

Many empirical studies have clearly demonstrated the effect of green growth in reducing carbon emissions. For example, Zhao et al. (2023) stated in their study on the Chinese economy that green growth has a statistically significant and negative effect on carbon emissions, emphasizing that green financing instruments play a decisive role in this process. Similarly, in an analysis conducted in G7 countries, Hao et al. (2021) showed that green growth policies supported by environmental taxes and renewable energy use significantly reduce carbon emissions. Deng et al. (2023) showed that in the economies that emit the most carbon, the efficiency of financial institutions and the development of markets are of significant importance in reducing carbon emissions through green growth. These findings show that green growth strategies can be a powerful policy tool in achieving emission reduction targets in both developed and developing countries.

Saleem et al. (2022), in their studies conducted on Asian countries, stated that green growth not only contributes to economic growth but also improves environmental quality and reduces carbon emissions. This finding was also confirmed by Wei et al. (2023) in the sample group called "green future countries"; the researchers revealed that green growth both directly reduces carbon emissions and systematically strengthens environmental sustainability. Amara and Qiao (2023), on the other hand, emphasize that green growth can reduce carbon emissions without compromising economic growth and thus contributes to the balanced achievement of sustainable development. These studies show that green growth offers important opportunities not only in terms of environmental but also economic sustainability.

On the other hand, the environmental impacts of green growth are not limited to carbon emissions; positive effects have also been found on broader environmental quality indicators such as the ecological footprint. For example, Dam et al. (2024) showed in their analysis of OECD countries that green growth is effective in reducing both per capita CO_2 emissions and ecological footprint. Similarly, Hassan et al. (2023) found that green growth supported by environmental innovation and natural resource management reduces the environmental pressure of countries and leads to improvements in ecological footprint indicators. These results show that multidimensional criteria, not just emissions-focused, should be taken into account when evaluating the environmental impacts of green growth.

Finally, in a comprehensive study, Saqib et al. (2024) examined environmental innovation, financial development, and green growth within a unified framework and reported that the combined effect of these factors strengthens environmental sustainability, reduces carbon emissions, and alleviates ecological pressures. Overall, these findings suggest that green growth is positively associated with environmental quality and can be regarded as an effective policy tool for achieving emission reduction and ecological sustainability objectives. In this context, green growth emerges as a strategic approach that should occupy a central position in environmental policymaking.

2.2. Relationship between green innovation and environmental quality

Numerous studies examining the impact of green innovation on environmental quality show that this innovative approach plays an important role in reducing carbon emissions and ensuring ecological sustainability (Yazıcı and Çiçeklioğlu 2025). Studies such as Zhao et al. (2025), Zhao et al. (2024) and Liu et al. (2022) have revealed in their analyses of Chinese data that green innovation both directly reduces carbon emissions and reduces emission intensity. These studies emphasize that technological developments strengthen the effect of carbon reduction over time and that the digital economy plays a supporting role in this process. In particular, in analyses using spatial and threshold models, it has been concluded that the impact of green innovation on emissions may vary according to regional and threshold levels.

Similarly, studies such as Afshan and Yaqoob (2023), Ali et al. (2022) and Wen et al. (2021) have also revealed the positive effects of green innovation on environmental quality in their studies on BRICS and South Asian countries. These studies state that green innovation is a balancing factor for factors with high potential for environmental damage, such as industrialization and openness to the outside world. Meng et al. (2022) emphasized that the potential for green innovation to increase environmental quality increases even more in the presence of environmental regulations. This finding shows that supportive regulations at the policy level can strengthen the positive impact of green technologies on the environment.

It is frequently emphasized in the literature that green innovation has an impact not only on carbon emissions but also on broader environmental indicators such as ecological footprint. Koseoglu et al. (2022) revealed that green innovation is directly effective in reducing the ecological footprint in their analysis of 20 most innovative countries. Ke et al. (2022) conducted an empirical study in 283 Chinese cities and showed that the increase in green innovation efficiency positively affects the environmental carrying capacity of cities and reduces footprint pressure. Such findings suggest that green innovation affects not only carbon emissions but also a wider range of components of environmental sustainability.

In addition, studies such as Zhang and Yasin (2024) and Khurshid et al. (2023) reveal that the impact of green innovation on the ecological footprint and carbon emissions can be further strengthened with financial instruments and policy structures. It has been found that green innovation strategies, especially those implemented together with carbon pricing, incentives and environmental taxes, create more significant improvements in environmental impacts. These results show that green innovation, not alone but together with effective governance and an environmental policy framework, can increase its impact on environmental quality.

As a result, the existing literature reveals that green innovation is an effective tool in both reducing carbon emissions and ecological footprint. In general, studies show that investments in innovative and environmentally friendly technologies reduce the pressure on the environment and make significant contributions to achieving sustainable development goals. However, it is also a common finding that green innovation should be supported by appropriate policies, financial instruments and governance mechanisms in order to maximize its impact.

2.3. Relationship between energy productivity and environmental quality

Energy efficiency is considered a strategic determinant in terms of environmental sustainability (Yazıcı et al. 2025). Wahab et al. (2021) stated that energy efficiency is effective in limiting trade-related carbon emissions and that this relationship is further strengthened by technological innovations. Ahmad et al. (2022) also found a negative relationship between energy efficiency and environmental quality and emphasized that the increase in energy efficiency can reduce carbon emissions even with the effect of economic globalization. Similarly, Xie and Jamaani (2022) showed that energy efficiency plays an important role in limiting emissions in developed economies, together with green innovation and environmental taxes.

Country-based studies also reveal the effects of energy efficiency on the environment in detail. For example, Kirikkaleli and Ali (2024) stated that energy efficiency makes a strong contribution to environmental sustainability in Germany; Addai et al. (2022) revealed that the increase in energy efficiency significantly reduces environmental degradation based on Fourier analysis in Germany. Kirikkaleli et al. (2023a) showed that energy efficiency positively affects environmental quality in Sweden with both linear and nonlinear modeling techniques. Similarly, Kirikkaleli and Sowah Jr (2023) in Finland and Kirikkaleli et al. (2023c) in Ireland showed that energy efficiency increases environmental quality in the long term.

The asymmetric effects of energy efficiency on environmental impacts are also prominent in the literature. Kirikkaleli et al. (2023c) examined both symmetric and asymmetric effects of energy efficiency on environmental quality in their study in Portugal and stated that this relationship has become more complex in the age of industrialization and digitalization. Liu et al. (2023) investigated the effects of energy efficiency on environmental sustainability together with economic growth in Southern European countries and found a positive relationship. Oyebanji and Kirikkaleli (2022) also showed the effect of energy efficiency on limiting emissions together with environmental regulations in the case of Greece.

The findings on the effects of energy efficiency on the ecological footprint are also remarkable. In their study covering 283 cities in China, Ke et al. (2022) showed that increasing energy efficiency directly reduces ecological pressure and causes less damage to the carrying capacity of cities. Similarly, Zhang et al. (2023) showed that energy efficiency contributes to more efficient use of natural resources and reduction of carbon emissions in the case of Morocco. Ge and Mehmood (2024), in their study conducted across OECD countries, emphasized the effect of energy efficiency on improving environmental quality within the framework of the environmental carrying capacity curve.

In conclusion, the existing literature strongly suggests that energy efficiency positively affects both carbon emissions and broader environmental indicators. However, many studies also indicate that this relationship is not linear and varies depending on countries, periods and regulatory policies (Kirikkaleli et al. 2023b; Safi et al. 2023). Therefore, considering energy efficiency in an integrated manner with environmental policies and tqaking regional differences into account will enable the development of more effective sustainability strategies.

2.4. Relationship between industrialization and environmental quality

The impact of industrialization on environmental quality is largely evaluated as negative in the literature. Opoku and Aluko (2021) showed that industrialization increases environmental degradation more, especially in low-emission countries, using panel quantile regression. Similarly, Elfaki et al. (2022) show that industrialization significantly increases carbon emissions in the case of ASEAN+3 countries. Ahmed et al. (2022) emphasize that industrialization is one of the main factors that increase carbon emissions in the Asia-Pacific region.

Vo et al. (2024) stated in their study on Vietnam that industrialization has negative effects on environmental quality and that this effect increases even more with urbanization. Musah and Yakubu (2022) also stated in the case of Ghana that industrialization poses a threat to environmental sustainability and that the environmental impacts of industrial activities should be limited with policy support. Rehman et al. (2021) found that industrialization in Pakistan increased carbon emissions along with energy imports and economic growth. Some studies emphasize that the environmental impacts of industrialization may vary depending on policy and structural factors. While Nkemgha et al. (2024) found that the environmental impacts of industrialization decreased as the stringency of environmental policies increased in Sub-Saharan Africa, Kwakwa (2022) showed that industrialization increased carbon emissions together with government spending and militarization in the case of Ghana. Aslam et al. (2021) stated that industrialization in China polluted the environment more with the increase in per capita income; Ali et al. (2025) stated that industrialization in Saudi Arabia created heterogeneous effects on carbon emission intensity.

In addition, studies examining the impact of industrialization on the ecological footprint also show that industrial activities increase the pressure on natural resources. Quito et al. (2023) suggest that industrialization increases the ecological footprint at the global level, while Li and Zhang (2023) suggest that this impact can be limited by institutional quality and renewable energy use. In conclusion, most of the literature agrees that industrialization negatively affects environmental quality; however, the level of this impact may vary depending on country conditions and environmental policies implemented.

3. Methodology

3.1. Dataset

The aim of this study is to examine the impact of green growth, green innovation, energy efficiency and industrialization on trade-adjusted carbon emissions (*TAEM*). In the study, annual data for the period 2003-2023 of 15 countries (Sweden, Finland, South Korea, Singapore, Switzerland, Netherlands, United States, Germany, United Kingdom, China, France, Denmark, Canada, Japan and Israel) that are among the most innovative countries in the world were analyzed. In this context, the impact of green innovation and energy efficiency in reducing carbon emissions is comprehensively evaluated using advanced econometric methods such as dynamic panel data analysis, together with the role of the industrialization process on environmental sustainability.

The study employs *TAEM* as the main dependent variable. *TAEM* is a measure that takes into account not only the production processes within a country's own borders, but also the carbon footprint transferred and imported through international trade (Jiang et al. 2022). While traditional carbon emissions are based on the total greenhouse gas emissions produced within a country's borders, *TAEM* allows for a more fair and accurate measurement of global carbon distribution by also taking into account emissions released during the production processes of traded goods (Zaka et al. 2025). Although developed countries, in particular, appear to have reduced their national emissions by shifting high-carbon-intensity production activities to developing countries, the *TAEM* approach provides a more holistic assessment by taking this carbon leakage into account. Another important advantage of *TAEM* is that it can directly measure the environmental impacts of international trade and contribute to the evaluation of the effectiveness of sustainable trade policies and green financing mechanisms (Li et al. 2023). Therefore, while traditional carbon emissions only provide an analysis at a local scale, *TAEM* helps to make environmental policies more inclusive and effective by revealing global emission dynamics.

In this study, green growth (*GG*), green innovation (*GIN*), energy efficiency (*EP*), and industrialization (*IND*) are employed as the explanatory variables. Green growth is measured by the share of renewable energy supply in total energy supply. Green innovation is proxied by the percentage of environmentally related technological inventions in total inventions worldwide. Energy efficiency is measured by the share of renewable energy in total energy supply, while industrialization is represented by the share of industry in gross domestic product (*GDP*).

Consistent with previous studies (Jiang et al. 2022; Li et al. 2023; Zaka et al. 2025), a logarithmic regression model shown in Equation (1) was used to estimate the proposed relationships. The definitions, measurement approaches, and data sources of all variables included in the analysis are presented in Table 1, which provides a comprehensive overview of the indicators used for green growth, green innovation, energy efficiency, and industrialization.

$$TAEM_{i,t} = \beta_0 + \beta_1 GG_{i,t} + \beta_2 GIN_{i,t} + \beta_3 EP_{i,t} + \beta_4 IND_{i,t} + \varepsilon_{i,t} \tag{1}$$

Table 1. Variables used in the study

Variables	Symbol	Measure	Source
Trade-adjusted emissions	TAEM	Consumption emissions in Mt CO2	Global Carbon Atlas
Green growth	GG	Renewable energy supply, % total energy supply	OECD
Green innovation	GIN	Development of environment-related technologies, % inventions worldwide	OECD
Energy productivity	EP	Renewable energy supply as % of total energy supply	OECD
Industrialization	IND	Industry value added (% of GDP)	WDI

3.2. Method

Cross-sectional dependence was tested using Breusch-Pagan LM, Pesaran et al. (2004) scaled LM, and Pesaran et al. (2008) adjusted LM tests to identify common shocks across countries and ensure result reliability. The calculation procedures are presented in Equations (2)-(5):

$$LM = T \sum_{i=1}^{N-1} \sum_{j=i+1}^{N} \hat{\rho}_{ij}^{\,2} \tag{2}$$

$$CD_{LM} = \sqrt{\frac{1}{N(N-1)}} \sum_{i=1}^{N-1} \sum_{j=i+1}^{N} \left(T\hat{\rho}_{ij}^{\,2} - 1\right) \tag{3}$$

$$CD = \sqrt{\frac{2T}{N(N-1)}} \left(\sum_{i=1}^{N-1} \sum_{j=1+1}^{N} \hat{\rho}_{ij} \right) \tag{4}$$

$$LM_{adj} = \left(\frac{2}{N(N-1)}\right)^{1/2} \sum_{i=1}^{N-1} \sum_{j=i+1}^{N} \hat{\rho}_{ij}^2 \frac{(T-K-1)\hat{\rho}_{ij} - \hat{\mu}_{Tij}}{\upsilon_{Tij}} \sim N(0,1) \tag{5}$$

Slope homogeneity was tested using Pesaran and Yamagata (2008) Δ tests, while Blomquist and Westerlund (2013) Δ tests were employed to account for heteroskedasticity and serial correlation, ensuring more reliable results. Calculations are shown in Equations (6)-(9):

$$\Delta_{HAC} = \sqrt{N}\left(\frac{N^{-1}S_{HAC} - k}{\sqrt{2k}}\right) \tag{6}$$

$$S_{HAC} = \sum_{i=1}^{N} T(\hat{\beta}_i - \hat{\beta})'(\hat{O}_{iT}V_{iT}^{-1}\hat{O}_{iT})(\hat{\beta}_i - \hat{\beta}) \tag{7}$$

$$\hat{\beta} = \left(\sum_{i=1}^{N} T\hat{O}_{iT}V_{iT}^{-1}\hat{O}_{iT}\right)^{-1} \sum_{i=1}^{N} \hat{O}_{iT}\hat{V}_{iT}^{-1}X_i' M_T y_i \tag{8}$$

$$\hat{V}_{iT} = \hat{\Gamma}_i(0) + \sum_{j=1}^{T-1} K\left(\frac{j}{M_{iT}}\right)[\hat{\Gamma}_i(j) + \hat{\Gamma}_i(j)'] \tag{9}$$

The stationarity of the panel data was tested using Pesaran's (2007) CADF and CIPS unit root tests, which account for cross-sectional dependence and yield more reliable results. Equations (10)-(14) present the related calculations.

$$\Delta y_{it} = \alpha_i + \beta_i y_{i,t-1} + u_{it} \tag{10}$$

$$u_{it} = \gamma f_t + \varepsilon_{it} \tag{11}$$

$$\Delta y_{it} = \alpha_i + \rho_i y_{i,t-1} + d_0 \bar{y}_{t-1} + d_1 \Delta \bar{y}_t + \varepsilon_{it} \tag{12}$$

$$\Delta y_{i,t} = \alpha_i + \rho_i y_{i,t-1} + c_i \bar{y}_{t-1} + \sum_{j=0}^{p} d_{i,j} \Delta \bar{y}_{t-j} + \sum_{j=0}^{p} \beta_{i,j} \Delta y_{i,t-j} + \mu_{i,t} \tag{13}$$

$$IPS = \frac{1}{N}\sum_{i=1}^{N} CADF_i \tag{14}$$

Westerlund (2005) test was applied to identify long-run relationships, while Westerlund's (2007) test further analysed panel cointegration using four ECM-based statistics. Equation (15) presents the long-run equilibrium model, and cointegration detection allows long-run parameter estimation.

$$\Delta Y_{it} = \delta_i d_t + \alpha_i Y_{i,t-1} + \gamma_i X_{i,t-1} + \sum_{j=1}^{pi} \alpha_{ij} \Delta Y_{i,t-1} + \sum_{j=-qi}^{pi} \gamma_{ij} \Delta X_{i,t-1} + \varepsilon_{it} \tag{15}$$

Long-run elasticity coefficients were estimated using SUR and Driscoll-Kraay (1998) methods. While SUR accounts for correlated errors, Driscoll-Kraay corrects for cross-sectional dependence and heteroskedasticity, providing robust results for panels with small N and heterogeneous structure. Calculations are shown in Equations (16)-(18):

$$\begin{aligned} y_1 &= x_1\beta_1 + u_1 \\ y_2 &= x_2\beta_2 + u_2 \\ &\vdots \\ y_M &= x_M\beta_M + u_M \end{aligned} \tag{16}$$

$$\begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_M \end{bmatrix} = \begin{bmatrix} X_1 & 0 & \dots & 0 \\ 0 & X_2 & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & X_M \end{bmatrix} + \begin{bmatrix} \beta_1 \\ \beta_2 \\ \vdots \\ \beta_M \end{bmatrix} + \begin{bmatrix} u_1 \\ u_2 \\ \vdots \\ u_M \end{bmatrix} \tag{17}$$

$$\Sigma = \begin{bmatrix} \sigma_{11} & \sigma_{12} & \dots & \sigma_{1M} \\ \sigma_{21} & \sigma_{22} & \dots & \sigma_{2M} \\ \vdots & \vdots & \ddots & \vdots \\ \sigma_{M1} & \sigma_{M2} & \dots & \sigma_{MM} \end{bmatrix} \tag{18}$$

The Panel-Corrected Standard Errors (PCSE) method (Beck and Katz 1995) was used to address heteroskedasticity and cross-sectional dependence, providing more robust estimates than Pooled OLS by modelling the error covariance matrix. The computation process is presented in Equations (19)-(21):

$$y_{it} = x_{it}\beta + \varepsilon_{it} \tag{19}$$

$$\begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_m \end{bmatrix} = \begin{bmatrix} X_1 \\ X_2 \\ \vdots \\ X_m \end{bmatrix} \beta + \begin{bmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \vdots \\ \varepsilon_m \end{bmatrix} \tag{20}$$

$$\Sigma[\varepsilon\varepsilon'] = \Omega = \begin{bmatrix} \sigma_{11}I_{11} & \sigma_{12}I_{12} & \dots & \sigma_{1m}I_{1m} \\ \sigma_{21}I_{21} & \sigma_{22}I_{22} & \dots & \sigma_{2m}I_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ \sigma_{m1}I_{m1} & \sigma_{m2}I_{m2} & \dots & \sigma_{mm}I_{mm} \end{bmatrix} \tag{21}$$

In the fifth stage, the Dumitrescu and Hurlin (2012) panel causality test was applied. As a second-generation test with bootstrap properties, it evaluates causal relationships using $\bar{Z}$ and $\bar{W}$ statistics against bootstrap critical values. The computation process is presented in Equations (22)-(24):

$$y_{i,t} = \alpha_i + \sum_{k=1}^{K} \beta_{ik}\, y_{i,t-k} + \sum_{k=1}^{K} \gamma_{i,k}\, X_{i,t-k} + \varepsilon_{it} \tag{22}$$

$$\bar{W} = \frac{1}{N} \sum_{i=1}^{N} W_i \tag{23}$$

$$\bar{Z} = \sqrt{\frac{N}{2K}} (\bar{W} - K) \tag{24}$$

4. Empirical findings and discussion

This section includes empirical findings on the impact of green growth, green innovation, energy efficiency and industrialization on *TAEM*.

Table 2. Cross-sectional dependence test results

Variables	TAEM	GG	GIN	EP	IND
B-P LM	189.8*	147.1*	428.3*	198.7*	128.1*
Pesaran scaled LM	19.8*	10.5*	21.9*	39.4*	15.8*
B-C scaled LM	28.3*	19.8*	36.52*	32.6*	12.8*
Pesaran CD	7.8*	10.9*	9.25*	7.75*	6.8*

According to Table 2 and Table 3, the results of the cross-sectional dependence tests for the variables show that all tests are statistically significant. This reveals that there is a strong horizontal cross-section dependence among the variables. Similarly, the tests for long-run models also confirmed the existence of horizontal cross-section dependence. These results suggest that common shocks may be effective in the series and methods that take into account horizontal cross-sectional dependence should be preferred instead of traditional panel estimation methods.

Tablo 3. Cross-sectional dependence test results

Tests	Model
LM	40.5*
LM adj*	20.8*
LM CD*	8.4*

The slope homogeneity test results in Table 4 show that the slope coefficients in the models are not homogeneous. The fact that both tests are statistically significant reveals that the relationships between variables differ across countries or units. In this case, it would be more appropriate to use methods that take heterogeneity into account instead of methods based on the assumption of homogeneous coefficients in panel data analysis.

Table 4. Slope homogeneity test

	Model
$\tilde{\Delta}$	5.9*
$\tilde{\Delta}_{adj}$	4.7*

According to the unit root test results presented in Table 5, CADF and CIPS tests show that the variables are non-stationary at level, but become stationary when first differences are taken. When the first differences of the series are taken, the test statistics become significant and stationarity is ensured, which leads to the acceptance of the alternative hypothesis (H_1: The series are non-stationary). Accordingly, it is determined that the variables have I(1) process and are suitable for econometric analysis. Based on these stationarity properties, the subsequent cointegration results reported in Table 6 provide further insights into the long-run equilibrium relationships among the variables.

Table 5. CIPS and CADF test

Variables	CADF		CIPS	
	I(0)	I(1)	I(0)	I(1)
TAEM	-0.8	-4.1*	-0.7	-4.8*
GG	-1.1	-5.2*	-0.9	-4.8*
GIN	-0.7	-2.9*	-0.8*	-3.4*
EP	-1.2	-5.5*	-1.0	-5.6*
IND	-0.8	-3.8*	-0.9*	-4.2*

Westerlund cointegration test results strongly support the existence of a long-run relationship between variables in the panel data set. Westerlund's variance ratio test is also consistent with these findings. Moreover, the results of the Westerlund (2007) ECM test confirm that there is a strong cointegration relationship between the variables by correcting the short-term deviations in the long run, as all statistics at both group and panel level are negative and large at the 1% significance level.

Table 6. Westerlund (2007) ECM test results

Statistic	Value	Z-value
G_t	-6.8	-6.1*
G_a	-14.7	-7.2*
P_t	-13.8	-7.5*
P_a	-15.2	-6.8*

In Table 7, the long-run estimator results are obtained by SUR, PCSE and D-K methods and all variables are statistically significant at 1% significance level. According to the long-run estimator results, there is a negative and statistically significant relationship between the Green Growth (*GG*) variable and Trade-Adjusted Emissions (*TAEM*). Since the coefficient of the *GG* variable is negative in all methods and at 1% significance level, an increase in green growth reduces trade-adjusted carbon emissions. This finding suggests that sustainable development policies and green growth strategies can reduce the trade-related carbon footprint. Green growth is effective in reducing carbon emissions by promoting environmentally friendly production processes and increasing the use of clean energy. The results reveal that it is important for countries to integrate their economic growth targets with sustainable development principles in order to control carbon emissions. This finding is consistent with various studies in the literature. For example, Dong et al. (2022) state that green growth in China is effective in reducing carbon emissions. Similarly, Zhao et al. (2023) emphasise the role of green finance in reducing carbon emissions through green growth. Dogan et al. (2022), Saleem et al. (2022), and Wei et al. (2023) collectively emphasize that green growth, green finance, and renewable energy transition play a crucial role in reducing carbon emissions and enhancing environmental quality, thereby contributing significantly to the achievement of sustainable development goals.

Table 7. Long-term estimator results

Variables	SUR	PCSE	D-K
GG	-0.122*	-0.138*	-0.119*
GIN	-0.091*	-0.089*	-0.095*
EP	-0.152*	-0.162*	-0.148*
IND	1.057*	1.108*	1.128*
Constant	-1.862*	-1.681*	-1.565*
Wald $\chi 2$	195.25	204.25	201.58
P	0.000	0.000	0.000
Obs.		315	

It shows that there is a negative and statistically significant relationship between green innovation and trade-adjusted emissions. Since the coefficients of the *GIN* variable are negative in all methods and at 1% significance level, an increase in green innovation leads to a decrease in *TAEM*. This finding suggests that the adoption of innovative and environmentally friendly technologies can reduce trade-related environmental impacts by reducing carbon emissions. Green innovation plays an important role in limiting trade-related carbon emissions by promoting energy-efficient technologies, cleaner production processes and low-carbon industrial practices. This result suggests that green innovation policies and the promotion of sustainable technologies will help countries both sustain economic growth and achieve environmental goals. This finding is consistent with various studies in the literature. For example, Kirikkaleli and Adebayo (2024) find that green finance and green innovation play important roles in improving environmental quality in Brazil. Similarly, Aneja et al. (2024) state that clean energy and green innovation are effective in ensuring environmental sustainability in G-20 countries. Furthermore, Ali et al. (2022) show that *FDI* and green innovation improve environmental quality in BRICS economies. Meng et al. (2022) emphasise the positive effects of capital formation, green innovation and renewable energy consumption on environmental quality. Finally, Khurshid et al. (2023) reveal that green innovation, together with carbon pricing and environmental policies, make significant contributions to reducing carbon emissions and achieving sustainable development goals in Central and Eastern European countries. All of these studies support that green innovation is an important factor in reducing carbon emissions and ensuring environmental sustainability.

It shows that there is a negative and statistically significant relationship between energy efficiency (*EP*) and *TAEM*. Since the coefficients of the *EP* variable are negative in all methods and at 1% significance level, increasing the share of renewable energy in total energy supply reduces trade-adjusted carbon emissions. This result shows that increasing the use of renewable energy instead of fossil fuels directly reduces carbon emissions. The transition to renewable energy strengthens environmental sustainability by encouraging the adoption of lower emission technologies in power generation. Moreover, the expansion of renewable energy-based generation can reduce the carbon footprint by contributing to the reduction of trade-related emissions. The results show that increasing the importance of renewable resources in energy supply is an important strategy for both economic growth and carbon reduction. These results are in line with various studies in the literature. Wahab et al. (2021) found that energy efficiency and technological innovation play an important role in limiting trade-induced carbon emissions and emphasised that increasing energy efficiency is an effective policy instrument for carbon mitigation. Xie and Jamaani (2022), on the other hand, found that green innovation, energy efficiency and environmental taxes reduce carbon emissions in developed economies and emphasised the importance of these factors in achieving sustainable development goals. Similarly, Zhang et al. (2023) found that energy intensity and energy efficiency directly affect carbon emissions in the Moroccan economy and that increasing energy efficiency supports environmental sustainability. Furthermore, Amin et al. (2022) examined the link between consumption-based carbon emissions and energy efficiency and eco-innovation in N-11 countries and showed that energy efficiency is a key factor in reducing carbon emissions. Ahmadi and Frikha (2023) evaluated the impact of carbon emissions on energy efficiency in G7 countries and revealed that sustainable energy policies should be developed. All of these studies support that increasing the use of renewable energy and improving energy efficiency are important factors in reducing trade-related carbon emissions and ensuring environmental sustainability. The findings emphasise the need to increase investments in renewable energy and strengthen energy efficiency policies to reduce carbon emissions.

Industrialisation (*IND*) has a positive and statistically significant relationship with $TAEM$. This finding suggests that the growth of the industrial sector increases trade-related carbon emissions. Increasing industrial production is generally associated with higher energy consumption, increased dependence on fossil fuels and higher carbon intensity. Especially heavy industry and energy-intensive sectors cause more carbon emissions through global trade. However, the environmental impact of industrialisation may vary depending on the technologies used in production processes and the sustainability of energy resources. The use of more environmentally friendly technologies and renewable energy sources can be effective in reducing the carbon footprint of the industrial sector. These results reveal that greener and more sustainable production methods should be adopted in the industrial sector. Developing green industrialisation policies, increasing energy efficiency measures and transition to low-carbon production processes can play an important role in reducing trade-related carbon emissions. These findings are consistent with various studies in the literature. Elfaki et al. (2022) found that industrialisation increases carbon emissions in ASEAN+3 economies and this effect may vary depending on industrial policies. Rehman et al. (2021) showed that industrialisation in Pakistan, combined with energy imports and economic growth, significantly increases emissions. Xiu (2025) states that in the Chinese economy, supply chain and digitalisation combine with industrialisation to increase energy consumption and lead to environmental pollution. However, some studies also point to factors that can reduce the environmental impacts of industrialisation. Nkemgha et al. (2024) found that industrialisation in Sub-Saharan Africa negatively affects environmental quality, but strict environmental regulations and policies can mitigate this impact. Aquilas et al. (2024) found that the use of renewable energy plays an important role in reducing the environmental impacts of industrialisation and that energy sources should be diversified for sustainable industrialisation. All of these studies show that industrialisation is an important factor in increasing carbon emissions and should be managed carefully in terms of environmental sustainability. However, promoting the use of renewable energy, adopting energy efficiency technologies and implementing strict environmental regulations can be effective in reducing the negative impacts of industrialisation. As a result, industrial policies should be organised in a way to encourage low-carbon production processes and green innovation.

Table 8. Dumitrescu-Hurlin panel bootstrap causality analysis

	W-bar	Z-bar	P
$TAEM \nrightarrow GG$	0.50	0.63	0.805
$GG \nrightarrow TAEM$	2.15	4.25	0.000
$TAEM \nrightarrow GIN$	0.35	0.42	0.894
$GIN \nrightarrow TAEM$	2.87	5.85	0.000
$TAEM \nrightarrow EP$	0.89	1.09	0.285
$EP \nrightarrow TAEM$	3.41	6.28	0.000
$TAEM \nrightarrow IND$	2.45	2.89	0.001
$IND \nrightarrow TAEM$	2.87	5.64	0.000

According to the causal results of Table 8, there is a significant and unidirectional causal relationship from green growth variable to trade-adjusted carbon emissions. This finding indicates that green growth policies can directly affect trade-related carbon emissions and sustainable economic growth strategies can play an important role in emission reduction. Similarly, there is a significant and unidirectional causality from green innovation and energy efficiency variables to *TEC*. These results suggest that policies that promote environmental sustainability have the capacity to reduce carbon emissions.

A bidirectional causality relationship was found between industrialisation and *TEC*. In other words, it shows that increasing industrialisation increases carbon emissions. This shows that the environmental impacts of industrial production are significant depending on the energy intensity and carbon content of the energy sources used. On the other hand, it shows that trade-related emission levels can affect industrialisation policies and production processes. These results emphasise that industrial and environmental policies should be handled in harmony with each other and the importance of transition to low-carbon production models.

5. Conclusion and recommendations

This study examines the impact of green growth, green innovation and energy efficiency on trade-adjusted carbon emissions and provides important findings in terms of environmental sustainability policies of the most innovative countries. When the results of this study are evaluated in terms of the 15 most innovative countries in the world, it shows that these countries have significant advantages in environmental sustainability and green transformation, but they need to adopt stronger policies in the process of reducing carbon emissions. In particular, the carbon emission-reducing effect of green innovation and energy efficiency reveals that these countries need to accelerate their transition to a low-carbon economic model.

The most innovative countries, despite their technological capabilities and strong innovation potential, have yet to fully achieve their carbon neutrality targets. Although countries such as Germany, Sweden, Finland, and Denmark have made substantial investments in renewable energy, the carbon-intensive nature of their industrial sectors continues to limit significant reductions in emission levels. The findings of this study indicate that increasing the share of renewable energy in the energy supply is an effective strategy for reducing trade-adjusted carbon emissions. Therefore, these countries should adopt more comprehensive and strategically integrated renewable energy policies, particularly by promoting the use of renewable energy in energy-intensive industries and strengthening energy efficiency measures to further reduce carbon emissions.

Similarly, despite their leading positions in green innovation, major industrial economies such as the United States, China, and Japan continue to exhibit considerable dependence on fossil fuels. Since the results demonstrate that green innovation contributes significantly to lowering carbon emissions, these countries should allocate greater resources to the development and commercialization of clean energy technologies. In particular, policies that stimulate green innovation in carbon-intensive industrial sectors and accelerate the transition toward sustainable production systems should be further strengthened. For trade-oriented economies such as the Netherlands, Singapore, and South Korea, the implementation of border carbon adjustment mechanisms and other trade-related environmental regulations should receive greater policy attention. Given the positive role of green growth in reducing trade-adjusted carbon emissions, expanding green trade policies and incorporating environmentally friendly production standards into international trade agreements may further support emission reduction efforts. Overall, the findings suggest that the world's most innovative countries are well positioned to lead global carbon reduction efforts by taking stronger actions in renewable energy deployment, industrial transformation, and green trade policies. Promoting low-carbon production processes, accelerating the transition toward renewable energy, improving energy efficiency, and increasing investments in green innovation will be essential for enhancing environmental sustainability while simultaneously strengthening long-term economic resilience.

Based on these findings, several policy recommendations can be proposed for highly innovative economies. Greater emphasis should be placed on expanding investments in green innovation and energy efficiency while accelerating the environmental transformation of industrial production. Stronger collaboration between the public and private sectors should be encouraged to increase research and development activities in green technologies. At the same time, renewable energy investments should continue to be supported, and energy efficiency policies should be implemented more extensively across all sectors of the economy. The broader application of carbon pricing mechanisms may further encourage emission reductions in both the industrial and energy sectors. Overall, the findings indicate that innovative countries should place greater emphasis on green growth, green innovation, renewable energy, and energy efficiency strategies to achieve sustainable development objectives. By fully utilizing their technological capabilities and economic advantages, these countries have the potential to play a leading role in reducing trade-adjusted carbon emissions and accelerating progress toward global sustainable development goals.

This study examines the impact of green growth, green innovation and energy efficiency on trade-adjusted carbon emissions, but it has some limitations. First of all, since the study focuses on the 15 most innovative countries, the results are limited in terms of generalizability and similar analyses need to be conducted for countries with different development levels. Future studies can provide a more comprehensive framework by examining how firms implement green innovation and energy efficiency strategies at the micro level. In addition, long-term studies are needed to evaluate the impacts of environmental regulations and carbon pricing mechanisms on trade-adjusted carbon emissions. In this context, studies using different econometric methods and alternative variables can provide policy makers with more comprehensive and comparative analyses. While the study examines the impact of green growth, innovation and energy efficiency on emissions, it only considers the 15 most innovative countries, limiting generalizability and requiring additional research for different levels of development.

Declaration of competing interest

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

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ICT and sustainable futures in emerging economies: The roles of renewable energy and green growth in the load capacity factor

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ABSTRACT

Over the past 20 years, it has been widely recognized that there is a noticeable downward trend in environmental quality indicators of emerging economies. As a result, improving environmental quality has become a key issue for researchers and policymakers in these countries. In this context, the load capacity factor model considers renewable energy usage, ICT, industrialization, aging, and green growth as the main drivers. Thus, this study analyzes the drivers of environmental quality in emerging economies between 1995 and 2021 by applying new panel data techniques such as panel AMG and Dumitrescu-Hurlin bootstrap causality approaches. Our findings indicate the presence of cointegration between the series. Additionally, we find that renewable energy usage, ICT, aging and green growth contribute to improving environmental quality, while industrialization has a negative impact on environmental quality. The causality analysis provides supporting evidence for these findings. Therefore, our results offer valuable insights for policymakers in emerging economies on how to improve environmental quality.

1. Introduction

Economic growth is a key objective for countries aiming to improve living standards. However, growth-oriented production activities often lead to serious environmental degradation (Khurshid and Deng 2021; Sharma et al. 2021). Increasingly frequent and intense environmental events, such as heatwaves, wildfires, droughts, glacial melting, and rising sea levels, have heightened global concerns about the sustainability of ecosystems (Meirun et al. 2021; Opoku and Aluko 2021; Altintas et al. 2024). In response to these concerns, the global community has taken a series of coordinated actions starting with the 1972 Stockholm Conference, followed by the 1992 Rio Summit, the 1997 Kyoto Protocol, and most notably the 2015 Paris Agreement (Dogan et al. 2022; Hakkak et al. 2023). The Paris Agreement marked a significant turning point by establishing the 17 Sustainable Development Goals (SDGs), which offer a comprehensive roadmap to combat climate change and enhance environmental quality.

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These developments have significantly influenced academic and policy-driven research agendas that seek to understand and promote sustainable environmental practices. Among the various indicators used to measure environmental degradation, carbon emissions and the ecological footprint are most commonly employed (Danish et al. 2020; Namahoro et al. 2021; Chu and Tran 2022; Dunyo et al. 2024). Nonetheless, carbon emissions are criticized for failing to encompass the full spectrum of environmental impacts, while the ecological footprint is limited to assessing demand-side pressures on environment (Okezie et al. 2023; Pata et al. 2023). To overcome these limitations, the load capacity factor (LCF) has emerged as a more comprehensive metric. Calculated as the ratio of a country's biological capacity to its ecological footprint, an LCF value greater than 1 indicates sustainable environmental quality, whereas a value below 1 reflects unsustainable practices (Dam and Sarkodie 2023; Pata and Isik 2021). Figure 1 demonstrates the trajectory of the LCF in emerging market economies between 2000 and 2022. The data reveals a persistent trend below the sustainability threshold, with the LCF decreasing from 0.67 in 2000 to 0.53 in 2022, consistently remaining below the global average (WDI 2025). This decline underscores a gradual yet continuous deterioration in environmental quality within these economies. Although industrial development -heavily reliant on carbon-based fuels- has been pivotal for socioeconomic advancement, it presents significant challenges for achieving environmental sustainability (Ahmed et al. 2022; Caglar et al. 2024). Industrial activities are projected to drive energy demand to nearly 50% in developing countries, given that they already account for over 30% of global energy-related carbon emissions (UNIDO 2025).

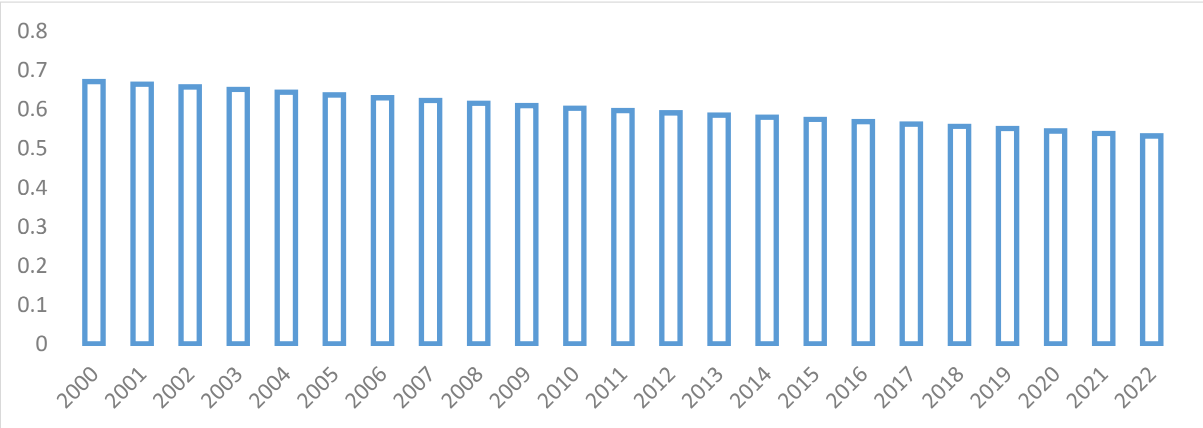

Figure 1. The course of load capacity factor in emerging market economies

Beyond industrialization, human-driven consumption and demographic changes also significantly impact environmental dynamics. In emerging economies striving to reach the standards of developed nations, rising per capita incomes have been accompanied by increased health expenditures (Fan et al. 2021; Udemba et al. 2024). Policies guided by SDG 3.8 (universal health coverage) and SDG 11 (sustainable cities and communities) have improved access to healthcare, housing, and transportation, thereby contributing to increased life expectancy and altering demographic profiles (Yang et al. 2021). The elderly population in emerging markets has more than doubled from 190 million in 2000 to 425 million in 2023, representing 53% of the global elderly population. This demographic shift necessitates a nuanced understanding of age-specific consumption patterns and their environmental implications (Guo et al. 2023). Despite efforts to accelerate environmental action through the 2015 Paris Agreement and the 2021 Glasgow Climate Conference, the fundamental challenge remains: how can countries balance economic growth with ecological sustainability? (Nejati and Shah 2023). This dilemma has spurred both researchers and policymakers to pursue sustainable development strategies with renewed urgency (Usman et al. 2021a; Sun et al. 2023). A crucial step in this direction is the adoption of SDG 9.2, which emphasizes sustainable industrialization. Through this framework, countries can enhance both production efficiency and environmental resilience while improving societal well-being (Lin and Ullah 2024).

A shift toward green economic growth-driven by technological innovation, renewable energy adoption, and increased energy efficiency is widely recognized as essential for environmental quality (Li et al. 2023a; Ibrahim et al. 2024). Investments aligned with SDG 9.4 have accelerated the integration of environmentally friendly technologies, particularly through expanded access to Information and Communication Technologies (ICT). In emerging economies, internet penetration rose from just 8% in 2000 to approximately 87% in 2023, 20% points higher than the global average (WDI 2025). Simultaneously, there has been a rapid uptake of renewable energy. As of 2023, emerging economies accounted for 51% of global wind energy consumption, 55% of global solar energy consumption, and substantial shares in geothermal and other renewables, amounting to over 580 million tons of oil equivalent (Energy Institute 2024). The growing consensus in the literature affirms the pivotal role of renewable energy in advancing sustainable development and mitigating environmental degradation (Salahuddin et al. 2020). While emerging markets are defined by rapid growth and increasing energy needs, transitioning from non-renewable to renewable sources remains central to any strategy for long-term environmental sustainability (Shrestha et al. 2022). Accordingly, green growth policies, which merge environmental priorities with economic development objectives, have gained prominence in academic and policy discourse (Zhao et al. 2023a; Zheng et al. 2023). ICT is similarly considered a vital enabler of environmental efficiency, enabling smarter resource management, real-time monitoring, and optimized energy usage (Iqbal et al. 2022). Danish et al. (2018) report that many emerging economies are proactively enhancing their ICT infrastructure through both domestic production and strategic imports, reflecting their ambition to become leaders in green technology.

Another underexplored yet important aspect of environmental policy is population aging. Contrary to common assumptions, aging populations may contribute positively to environmental sustainability due to reduced mobility, lower consumption levels, and greater demand for healthcare rather than industrial goods. The global elderly population, which stood at 723 million in 2021, is projected to reach 1.5 billion by 2050 (Wang et al. 2022a). As elderly demographics reshape consumption patterns and energy demand, it becomes imperative to incorporate aging-related considerations into environmental policy design (Quan et al. 2025). In this context, emerging markets must not only address the pressures of industrialization and urbanization but also adapt to the evolving demographic landscape to ensure long-term environmental quality. Based on these dynamics, this study aims to address the following key research questions for emerging market economies:

1. Does renewable energy consumption improve environmental quality?
2. Does ICT have a positive impact on environmental quality?
3. What is the relationship between population aging and environmental quality?
4. Does green growth positively affect environmental quality?
5. How does industrialization affect environmental quality?

Our study has the potential to make several important contributions to the existing literature. In line with this objective, it investigates the impacts of renewable energy consumption, information and communication technologies (ICT), population aging, green growth, and industrialization on environmental quality in emerging market economies over the period 1995-2021. First, the study develops a comprehensive empirical framework by simultaneously incorporating renewable energy consumption, ICT, population aging, green growth, and industrialization as key determinants of environmental quality. To the best of our knowledge, this is among the few studies that jointly examine these factors within a unified framework, thereby extending and enriching the empirical literature on environmental sustainability in emerging economies. Second, unlike previous studies that predominantly employ carbon emissions or ecological footprint as proxies for environmental degradation (e.g. Zhan et al. 2023; Wei et al. 2023; Yuan et al. 2024), this study contributes to the literature by utilizing the load capacity factor (LCF) as a more comprehensive indicator of environmental sustainability. Since the load capacity factor captures both ecological demand and biocapacity, it provides a broader perspective on environmental quality and facilitates the formulation of more effective and evidence-based environmental policies. Third, the study employs a set of advanced second-generation panel econometric techniques that explicitly account for cross-sectional dependence and slope heterogeneity, thereby enhancing the reliability and robustness of the empirical findings. In particular, the long-run equilibrium relationship among the variables is examined using the Westerlund (2007) cointegration approach, while long-run coefficient estimates are obtained through the Augmented Mean Group (AMG) estimator proposed by Eberhardt and Bond (2013) and the Fully Modified Ordinary Least Squares (FMOLS) estimator developed by Pedroni (2004). The combined use of AMG and FMOLS estimators provides more robust and comparable long-run estimates. Furthermore, causal interactions among the variables are investigated using the bootstrap panel causality approach of Dumitrescu and Hurlin (2012). Finally, the empirical findings reveal that renewable energy consumption, ICT, population aging, and green growth contribute positively to environmental quality, whereas industrialization exerts an adverse effect. By providing robust evidence on the environmental implications of these factors, the study is expected to offer valuable insights for policymakers and substantially contribute to the growing body of literature on sustainable development and environmental sustainability in emerging market economies.

The remainder of this paper is structured as follows: Section II outlines the theoretical framework and reviews the relevant literature. Section III presents the data, model, and methodology. Section IV discusses the empirical findings. Finally, Section V concludes the study and provides policy recommendations.

2. Theeretical framework and literature review

2.1. Renewable energy-environmental quality nexus

Since the 18th century, global energy dependency has increasingly relied on fossil fuels, contributing significantly to environmental degradation (Yuan et al. 2023). Contemporary empirical research identifies non-renewable energy consumption as one of the main drivers of anthropogenic climate change (Koengkan et al. 2020; Usman et al. 2021a). In contrast, renewable energy, derived from naturally replenishing and clean sources such as solar, wind, hydro, wave, and geothermal energy, does not emit greenhouse gases or hazardous waste, making it a crucial tool for mitigating environmental harm (Murshed et al. 2021; Deng et al. 2023; Wang et al. 2023).

Numerous empirical studies affirm the environmental benefits of renewable energy. For instance, Khurshid and Deng (2021) find that renewable energy consumption in newly industrialized countries reduces both production-based and consumption-based carbon emissions, thereby improving environmental quality. Similarly, Caglar et al. (2024), using CUP-FM and CUP-BC estimators, and Adebayo and Samour (2024), applying PMG and MG methods, demonstrate that renewable energy significantly increases the load capacity factor, a comprehensive indicator of environmental sustainability. Further supporting evidence comes from Shang et al. (2022) and Mehmood et al. (2023), who analyze G8 and ASEAN countries and report that renewable energy use positively contributes to environmental quality through CS-ARDL and AMG estimations. Awosusi et al. (2024), in a time-series analysis for Japan, confirm that renewable energy enhances the load capacity factor using ARDL, DARDL, FMOLS, and DOLS techniques. Similar conclusions are drawn by Hakkak et al. (2023) for Russia and Ibrahim et al. (2024) for the United States, where renewable energy reduces ecological footprint and carbon emissions, respectively. Collectively, these studies consistently highlight the vital role of renewable energy in advancing sustainable environmental outcomes.

2.2. ICT-environmental quality nexus

The rapid proliferation of Information and Communication Technologies (ICTs) in recent decades has transformed economic, social, and industrial systems. While digitalization has significantly improved productivity and resource efficiency, its environmental implications remain subject to scholarly debate (Godil et al. 2020). On one hand, the lifecycle of ICT products, from production to disposal, requires substantial energy input, which may lead to increased greenhouse gas emissions (Nejati and Shah 2023; Sampene et al. 2023). This perspective is supported by studies such as Sana et al. (2021) and Jakada et al. (2023), which find that ICT-related energy consumption exacerbates environmental degradation. On the other hand, ICT is also considered a tool for enhancing environmental efficiency. By facilitating telecommuting, online services, digital transactions, and intelligent energy systems, ICT reduces transportation demand and optimizes energy consumption (Batool et al. 2022; Zheng et al. 2023). Moreover, ICT enhances environmental awareness through improved access to information and education, thereby promoting eco-friendly behavior (Usman et al. 2021b).

Empirical studies reflect this dual perspective. For example, Awad (2022) finds that ICT reduces ecological footprint across 47 Sub-Saharan African countries. Similarly, Bibi et al. (2023) demonstrate that ICT reduces both carbon emissions and ecological footprint in China over the long term. Li et al. (2023b) report that ICT enhances the load capacity factor in Next-11 countries, while Kahouli et al. (2022) document similar effects for Saudi Arabia. Conversely, Bilal et al. (2022), analyzing 44 OBOR countries, reveal that ICT increases carbon emissions in the long run. Other studies, such as Chatti (2021), Raheem et al. (2020), and Yahyaoui (2024), using different ICT indicators (e.g. broadband, internet access, mobile subscriptions), conclude that ICT exacerbates environmental degradation. Li et al. (2023a) further identify an inverted U-shaped relationship, indicating that ICT's impact on environmental quality may vary across development stages. These mixed results highlight the need for context-specific strategies to harness ICT for environmental sustainability.

2.3. Industrialization-environmental quality nexus

Industrialization, a cornerstone of economic transformation, often involves a structural shift from agriculture to manufacturing and heavy industry. This transition is accompanied by increased exploitation of natural resources and higher energy consumption, leading to environmental challenges (Mahmood et al. 2020; Opoku and Aluko 2021). In regions lacking access to clean energy sources, industrial growth relies heavily on fossil fuels, intensifying carbon emissions and environmental degradation (Patel and Mehta 2023; Ouyang et al. 2020).

Empirical studies consistently show a negative relationship between industrialization and environmental quality. For instance, Kwakwa (2022) and Udemba and Keleş (2022), using the ARDL method for Ghana and Turkey, respectively, find that industrialization contributes to long-term carbon emissions. Similarly, Rehman et al. (2021) confirm that industrial activities increase CO_2 emissions across all quantiles in Pakistan. Ghazouani (2022) reaches the same conclusion for Tunisia, and Jin and Huang (2023) observe that industrialization reduces the load capacity factor in South Africa. Azam et al. (2022), focusing on six OPEC countries, report that industrialization promotes carbon emissions, with the Dumitrescu-Hurlin test confirming unidirectional causality. Usman and Balsalobre-Lorente (2022), examining newly industrialized countries using Driscoll-Kraay, PMG, AMG, and CCEMG estimators, find a consistent negative effect of industrialization on ecological footprint. Overall, the literature strongly indicates that unchecked industrial expansion poses a significant threat to environmental quality.

2.4. Aging-environmental quality nexus

Demographic shifts, particularly population aging, present complex implications for environmental sustainability. The elderly population may influence energy consumption and emissions patterns through lifestyle preferences and consumption habits. Two competing views dominate the literature. The first argues that older individuals, often retired and less mobile, contribute less to emissions due to reduced participation in economic production and preference for low-impact transportation (Guo et al. 2023; Fan et al. 2021; Yang et al. 2021). Conversely, the second view posits that aging populations may hinder environmental quality due to greater reliance on energy-intensive appliances, lower adaptability to new green technologies, and higher healthcare-related energy demand (Mehmood et al. 2022; Liu et al. 2022; Yu et al. 2018). Wang et al. (2022b), using a threshold panel approach for 134 countries, find that aging increases both carbon emissions and ecological footprint, with effects varying across income groups. Sun et al. (2023), employing MG, AMG, and CCEMG methods, report that aging improves environmental quality in East Asia by lowering CO_2 emissions. Alsaleh et al. (2023) and Yang et al. (2022a) also find that aging enhances environmental quality in the EU and G7 countries, respectively.

However, the relationship appears to be nonlinear. For example, Zhang and Tan (2016) and Yuan et al. (2024) document an N-shaped association in Chinese cities, while Yaqoob et al. (2024) report that aging reduces environmental degradation across 82 developing countries, with effects differing by income level. In Russia, Udemba et al. (2024) find that aging increases ecological footprint, suggesting country-specific policy implications. These findings highlight the importance of incorporating demographic dynamics into environmental planning.

2.5. Green growth-environmental quality nexus

Excessive reliance on fossil fuels has led to global environmental degradation, including biodiversity loss, glacier melt, and increasingly erratic weather patterns (Lin and Ullah 2023). As a response, green growth has emerged as a strategic framework that aims to reconcile economic progress with environmental protection. By promoting the efficient use of resources, supporting technological innovation, and encouraging renewable energy adoption, green growth strategies offer a sustainable development pathway (Wei et al. 2023; Dam et al. 2024; Khan et al. 2023).

Empirical research generally supports the positive influence of green growth on environmental quality. For instance, Dogan et al. (2022) and Saqib et al. (2024) show that green growth improves environmental quality in both environmentally progressive and high-footprint countries, respectively. Chen et al. (2023) report that green economic recovery efforts reduce carbon emissions in 22 developing Asian nations. Time-series analyses by Akther et al. (2024) for Bangladesh and Lin and Ullah (2024) for Pakistan confirm long-run improvements in environmental quality due to green growth, with evidence of bidirectional causality. In the United States, Chien et al. (2021) find that green growth reduces both CO_2 emissions and PM2.5 levels. Hassan et al. (2023), using ecological footprint data for G7 and E7 countries, and employing CS-ARDL and DCCE techniques, demonstrate that green growth significantly improves environmental conditions. Zhao et al. (2023a), studying China's provinces, highlight the role of regional heterogeneity in the green growth-environmental quality nexus. Finally, Chang et al. (2024) report that green growth enhances environmental quality in OECD countries based on Driscoll-Kraay and system GMM estimations. Collectively, these studies underscore the transformative potential of green growth strategies in achieving environmental sustainability.

3. Model, data and methodology

3.1. Model and data description

In developing economies, addressing environmental and climate issues, as well as investigating the underlying factors behind these issues, continues to be one of the main areas of interest for policymakers (Zhao et al. 2023b; Ali et al. 2023; Du et al. 2024). Similarly, this study tests the underlying factors of environmental issues (environmental quality) within the context of emerging market economies. In this framework, the main dependent variable is load capacity factor (*EQ*). The key independent variables chosen for the study are renewable energy usage (*REN*), information and communication technology (*ICT*), industrialization (*IND*), aging (*AGE*), and green economic growth (*GG*). Thus, in the analysis of the relationship between these variables, the following multivariate regression model is developed in Equation (1):

$$EQ_{it} = f(REN_{it}, ICT_{it}, IND_{it}, AGE_{it}, GG_{it}) \tag{1}$$

In this context, the subscripts *i* and *t* denote the cross-sectional units and the time period, respectively. To reduce potential heteroscedasticity, all dependent and independent variables are expressed in their natural logarithmic forms. This transformation enables the coefficients in the model to be interpreted as elasticities, specifically the elasticity of environmental quality with respect to renewable energy consumption, ICT, industrialization, aging, and green economic growth. Accordingly, the empirical model can be reformulated as follows in Equation (2):

$$lnEQ_{it} = \alpha + \gamma_1 lnREN_{it} + \gamma_2 lnICT_{it} + \gamma_3 lnIND_{it} + \gamma_4 lnAGE_{it} + \gamma_5 lnGG_{it} + \varepsilon_{it} \tag{2}$$

Here, α, ln, and ε_{it} represent the intercept, the natural logarithm, and the regression residuals, respectively. On the other hand, γ_1, γ_2, γ_3, γ_4 and γ_5 are used to estimate the elasticity coefficients. Most studies reveal a close relationship between renewable energy and environmental performance (Ali et al. 2023; Adebayo and Samour 2024). Since renewable energy use improves environmental quality by reducing environmental pollution, γ_1 is expected to take a positive value. This variable is measured as the share of renewable energy consumption in total final energy consumption. Considering both the deteriorating and improving effects of *ICT* on the environment, many studies employ it as an independent variable (Dogan and Pata 2022; Yahyaoui 2024). Therefore, the value of γ_2 can be either positive or negative. Here, *ICT* is represented by the share of individuals using the internet in the total population. According to Jin and Huang (2023), industrialization triggers environmental degradation and thus harms environmental quality. Therefore, γ_3 is expected to be negative. This variable can be measured as the share of industrial value added in *GDP*. Some studies in the literature discuss both the positive and negative environmental effects of population aging (Wang et al. 2017; Sun et al. 2023). Accordingly, γ_4 may take either *a* positive or *a* negative value. The share of the population aged 65 and above in the total population can be used as the measure of aging. Finally, since green growth has direct positive effects on improving environmental quality, γ_5 is expected to take *a* positive value (Zhao et al. 2023a; Chang et al. 2024). Carbon efficiency is widely used as a measure of green growth in many studies.

In the study, the cross-sectional dimension consists of 19 emerging market economies, while the time dimension covers the period from 1995 to 2021. The selection of this period is primarily driven by data availability, particularly because *REN* data are available only until 2021, whereas most explanatory variables are available from 1995 onwards. *EQ* data are obtained from the Global Footprint Network (GFN) (2025), while the datasets for *REN, ICT, IND,* and *AGE* are sourced from the World Bank (2025). *GG* data are retrieved from the Organization for Economic Cooperation and Development (OECD) (2025). Table 1 presents detailed information on the variables and data sources used in the study.

Table 1. Data descriptions

Variables	Symbol	Measure	Source	Expected sign
Load capacity factor	EQ	Per capita biocapacity/ecological footprint) (Pata and Isik 2021)	GFN	-
Renewable energy	REN	Renewable energy consumption (% of total final energy consumption) (Sun et al. 2025)	WDI	(+) (Ali et al. 2023)
Information and Communication Technology	ICT	Individuals using the internet (% of population) (Zhan et al. 2023)	WDI	(–) (+) (Dogan and Pata 2022)
Industrialization	IND	Industry value added (% of GDP) (Wang et al. 2022a)	WDI	(–) (Sun et al. 2024)
Aging	AGE	Population ages 65 and above (% of total population) (Boz and Ozsarı 2020)	WDI	(–) (+) (Wang et al. 2017)
Green growth	GG	CO_2 productivity (GDP per unit of energy related CO_2 emission) (Liu and Zhang 2024)	OECD	(+) (Zhao et al. 2023a)

Table 2. Summary statistics

Statistics	lnEQ	lnREN	lnICT	lnIND	lnAGE	lnGG
Mean	-0.249	1.158	1.135	1.487	0.879	0.616
Median	-0.324	1.209	1.461	1.493	0.826	0.664
Std. dev.	0.334	0.404	0.838	0.105	0.214	0.203
Min.	-0.974	-0.397	-2.304	1.125	0.535	0.017
Max.	0.586	1.705	1.989	1.686	1.352	0.973
Skewness	0.598	-1.034	-1.407	-0.722	0.539	-0.682
Kurtosis	3.230	4.144	4.524	4.180	2.071	2.781

Table 2 reports the descriptive statistics of the variables, whereas Table 3 presents the correlation matrix illustrating the pairwise relationships among them. The results reveal that *lnREN* and *lnGG* are positively correlated with *lnEQ*, while *lnIND* exhibits a negative correlation with *lnEQ*. In addition, *lnAGE* and *lnICT* are found to be negatively correlated with *lnEQ*, which appears to be inconsistent with the theoretical expectations proposed in the literature.

Table 3. Correlation matrix

Variables	lnEQ	LnREN	lnICT	lnIND	lnAGE	lnGG
lnEQ	1.000					
lnREN	0.647	1.000				
lnICT	-0.113	-0.251	1.000			
lnIND	-0.157	-0.127	-0.151	1.000		
lnAGE	-0.178	-0.217	0.477	-0.361	1.000	
lnGG	0.541	0.428	0.144	-0.210	-0.134	1.000

3.2. Methodology

First, to avoid biased and inconsistent results, we conduct a preliminary investigation into cross-sectional dependence (CSD) and slope heterogeneity. For CSD, we apply the approaches provided by Breusch and Pagan (1980), Pesaran (2004), and Baltagi et al. (2012). These approaches test the null hypothesis that there is no dependence among cross-sectional units. For the analysis of slope heterogeneity, we use the tests by Pesaran and Yamagato (2008) and Blomquist and Westerlund (2013). Both tests evaluate the null hypothesis that the slope coefficients are homogeneous. Second, the unit root analysis of the variables is conducted using Pesaran's (2007) cross-sectionally augmented ADF (CADF) test. This approach, which accounts for cross-sectional dependence, uses the regression model shown in Equation (3) below:

$$\Delta y_{it} = \alpha_i + \beta_i y_{it-1} + \gamma_i \hat{y}_{t-1} + \theta_i \Delta \hat{y}_t + \varepsilon_{it} \tag{3}$$

where $i = 1, \dots, N, t = 1, \dots, T$ and $\hat{y}_t$ denotes the cross-section means. In this process, the null hypothesis is $H_0: \beta_i = 0$ for all i, the alternative hypothesis is $H_1: \beta_i < 0$ for some i.

Following the stationrity analysis of the series, the cointegration analysis is conducted. For this purpose, the tests by Pedroni (2004) and Westerlund (2005; 2007) are employed. Pedroni and Westerlund are residual-based cointegration approaches, and in the application of both tests, cross-sectional averages are taken into account. The Westerlund (2007) test specifically focuses on CSD by incorporating a bootstrap procedure into the cointegration model. It presents four test statistics as specified in Equations (4)-(7) below:

$$G_t = \frac{1}{N} \sum_{i=1}^{N} \frac{T\alpha_i'}{SE(\alpha_i')} \tag{4}$$

$$G_a = \frac{1}{N} \sum_{i=1}^{N} \frac{\alpha_i'}{\alpha_i'(1)} \tag{5}$$

$$P_t = \frac{\alpha'}{SE(\alpha')} \tag{6}$$

$$P_a = T\alpha' \tag{7}$$

Fourth, our econometric strategy requires the estimation of long-run coefficients. For this purpose, the AMG estimator, introduced by Eberhardt and Bond (2013), is used as the primary estimation technique, while the FMOLS estimator by Pedroni (2004) is employed to support the findings from the AMG estimator. The AMG estimator is known as one of the second-generation approaches that can be used in cases of CSD and slope heterogeneity. To estimate the long-run coefficients of the variables, the AMG approach utilizes the following specification in Equation (8):

$$\hat{\beta}_{AMG} = N^{-1} \sum_{i=1}^{N} \hat{\beta}_i \tag{8}$$

Finally, to determine the existence and direction of causality between the variables, we use the bootstrap causality approach proposed by Dumitrescu and Hurlin (2012). This causality approach is preferred in cases of CSD and balanced panels. They contributed the test statistics shown in Equation (9)-Equation (10) to the literature:

$$\overline{W} = \frac{1}{N} \sum_{i=1}^{N} W_i \tag{9}$$

$$\bar{Z} = \sqrt{\frac{N}{2K}} (\overline{W} - K) \tag{10}$$

4. Empirical finding and discussion

Table 4 presents the results regarding CSD of the variables. Through tests based on the methodologies of Breusch and Pagan (1980), Pesaran (2004), and Baltagi et al. (2012), CSD is identified at the 1% significance level for the variables i.e. *lnEQ, lnREN, lnICT, lnIND, lnAGE,* and *lnGG.*

Table 4. Preliminary tests results

Panel A: The CSD analysis			
Variables	**Breusch-Pagan LM**	**Pesaran scaled LM**	**Bias-corrected scaled LM**
lnEQ	1543.249***	74.202***	73.837***
lnREN	1910.066***	94.037***	93.672***
lnICT	4327.896***	224.779***	224.413***
lnIND	1158.699***	53.408***	53.043***
lnAGE	4016-588***	207.945***	207.580***
lnGG	2086.601***	103.583***	103.218***

Panel B: The SH analysis		
Statistics	**Pesaran-Yamagata**	**Blomquist-Westerlund**
$\tilde{\Delta}$	11.776***	16.424***
$\tilde{\Delta}_{adjusted}$	13.682***	20.371***

Note: *** expresses significance at 1% level

Table 5. CADF unit root test results

Variable	**Constant**		**Constant and trend**	
	Level	**1st Difference**	**Level**	**1st Difference**
LnEQ	-2.019	-2.745***	-2.254	-2.696**
lnREN	-1.015	-3.242***	-2.200	-3.260***
LnICT	-1.981	-2.408***	-2.448	-2.815***
lnIND	-1.616	-3.329***	-2.367	-3.369***
lnAGE	-1.471	-2.531***	-2.025	-3.375***
LnGG	-1.703	-2.578***	-2.207	-3.456***

Note: ***, ** and * express significance at 1%, 5% and 10% level, respectively

The stationarity results of the variables are presented in Table 5. The examination of the CADF unit root test for both the constant and constant-trend models shows that the variables contain a unit root at their level values. However, when the variables are differenced, they become stationary. This indicates that the series are *I(1)*.

Table 6. Cointegration tests results

Westerlund (2007)	Value	Z-value	p-value
Gt	-12.734***	-46.138	0.000
Ga	-0.158	7.835	1.000
Pt	-12.304***	-1.814	0.000
Pa	-0.205	5.812	1.000
Pedroni (2004)		**Test statistic**	**p-value**
Modified PP t		0.321	0.374
PP t		-6.577***	0.000
Augmented DF t		-6.034***	0.000
Westerlund (2005)		**Test statistic**	**p-value**
Variance Ratio		-2.382***	0.008

Note: *** expresses significance at 1% level.

Table 6 presents the results of the cointegration relationship between the variables, including tests such as Pedroni (2004) and Westerlund (2005), as well as the Westerlund (2007) test, which allows for CSD and heterogeneity. According to the results, the group mean (*Gt*) and panel mean (*Pt*) statistics of Westerlund (2007), along with the *PPt, ADFt,* and Variance Ratio statistics, confirm that the variables exhibit a long-term equilibrium relationship. In other words, this indicates that the variables are cointegrated. Table 7 presents the long-term coefficient estimates from the AMG test. Our findings indicate that, in the long run, renewable energy, *ICT*, aging, and green growth promote environmental quality, while industrialization hinders environmental quality. Empirical findings reveal that renewable energy use positively affects load capacitiy factor. To elaborate, a 1% change in renewable energy consumption leads to a positive impact of 0.277% on environmental quality. Our finding is consistent with the results of Ge and Mehmood (2024) for OECD countries, and Sharma et al. (2021), for South Asia who note that renewable energy contributes to improving environmental quality. Similarly, ICT positively affects load capacitiy factor. A 1% increase in *ICT* leads to a 0.020% improvement in environmental quality. Our result is consistent with findings of Khan and Rehan (2022) and Jiang et al. (2024), who state that *ICT* contributes to environmental quality by reducing carbon emissions in China. However, it differs from the findings of Danish et al. (2018), who report that *ICT* harms environmental quality by increasing CO_2 emissions in the Next-11 countries.

Table 7. Model estimation with AMG

Variables	Coefficient	z-statiatics	p-value
lnREN	0.277*** (0.068)	4.08	0.000
lnICT	0.020** (0.080)	2.33	0.020
lnIND	-0.236** (0.097)	-2.43	0.015
lnAGE	0.973** (0.473)	2.05	0.040
lnGG	0.122* (0.071)	1.72	0.085
Constant	-0.865*** (0.330)	-2.62	0.009
Wald χ^2	35.21		
Prob.	0.000		
RMSE	0.032		

Note: ***, ** and **express significance at 1%, 5% and 10% level, respectively

Table 7 also provides information that industrialization decreases load capacitiy factor. A 1% increase in industrialization reduces environmental quality by 0.236%. Our empirical finding is consistent with the results of Sikder et al. (2022), who conduct research on developing countries, and Voumik and Sultana (2022), who study the BRICS countries. In both studies, industrialization reduces environmental quality by increasing carbon emissions. It is found that among the variables in the analysis, the one that contributes most to environmental quality is aging. Specifically, a 1% change in aging is determined to increase environmental quality indicator by 0.973%. Our finding is consistent with the results of Yang et al. (2022b), who find that aging reduces carbon emissions in G7 countries, and Tarazkar et al. (2021), who argue that aging declines environmental degradation in Middle Eastern countries. Lastly, Table 7 concerns the effect of green growth on environmental quality. Green growth raises load capacity factor. Keeping other things constant, a 1% increase in green growth stimulates environmental quality by 0.122%. Our long-term coefficient estimate is consistent with Chang et al. (2024) and Yikun et al. (2023), who report that green growth positively affects environmental quality by reducing carbon emissions. Table 8 presents the FMOLS estimation results. Our findings indicate that, in the long term, renewable energy, ICT, aging and green growth contribute to improving environmental quality, while industrialization hinders environmental quality. These results support the AMG test findings presented in Table 7. Further, Table 9 provides a summary of FMOLS and AMG test results.

Table 8. Robustness analysis (FMOLS method)

Variables	Coefficient	t-statiatics	p-value
LnREN	0.342^{***} (0.017)	20.017	0.000
LnICT	0.018^{**} (0.002)	7.809	0.020
LnIND	-0.167^{***} (0.058)	-2.850	0.004
LnAGE	0.742^{***} (0.112)	6.623	0.000
lnGG	0.073^{*} (0.040)	1.829	0.068

Note: ***, ** and **express significance at 1%, 5% and 10% level, respectively

Table 9. Summary of estimation outcomes

Variables	AMG	FMOLS
lnREN	(+) ✓	(+) ✓
lnICT	(+) ✓	(+) ✓
lnIND	(–) ✓	(–) ✓
lnAGE	(+) ✓	(+) ✓
lnGG	(+) ✓	(+) ✓

Note: ✓ expresses statistical significance of the coefficients

Table 10 presents the outcomes of causality test. According to the results, a one-way causality from renewable energy consumption to environmental quality is confirmed. This finding is consistent with Yang et al. (2023) for BRICS countries and Jahanger et al. (2024) for the top 10 countries in terms of sustainable development. They found that ICT is a cause of environmental quality. Our result diverges from the findings of Ganda (2024) and Sampene et al. (2023), who report the presence of bidirectional causality between ICT and environmental indicators in Sub-Saharan African and South Asian countries respectively. There is a unidirectional causality from industrialization to environmental quality. This finding is contrary Ahmed et al. (2022), who examine the industrialization-environment quality relationship for Pakistan, and Sumaira (2023), who investigate this relationship for South Asian countries. They noted that a bidirectional causality between the variables is observed.

The causality analysis reveals a bidirectional causality between aging and environmental quality. Our finding is consistent with Yang et al. (2021), who conduct research on OECD countries, and Chu (2024). They find the existence of a bidirectional causality between aging and environmental indicators. A bidircetional causal association is found between green growth and environmental quality. This result is consistent with Saleem et al. (2022) for Asian countries and Dam et al. (2024) for OECD countries. They noted the presence of bidirectional causality is observed between green growth and environmental quality indicators. We conduct 500 replications to calculate the bootstrapped p-values.

Table 10. Dumitrescu-Hurlin bootstrap causality analysis

Hypothesis	W-stat.	Zbar-stat.	p-value	Results
lnREN ≠> lnEQ	3.846	8.772**	0.006	lnREN → lnEQ
lnEQ ≠> lnREN	2.245	3.838	0.254	
lnICT ≠> lnEQ	7.533	8.068**	0.038	lnICT → lnEQ
lnEQ ≠> lnICT	1.549	1.693	0.472	
lnIND ≠> lnEQ	7.981	6.135**	0.046	lnIND → lnEQ
lnEQ ≠> lnIND	2.461	4.505	0.242	
lnAGE ≠> lnEQ	4.639	11.217***	0.008	lnAGE ↔ lnEQ
lnEQ ≠> lnAGE	5.886	15.061***	0.000	
lnGG ≠> lnEQ	2.704	5.254*	0.070	lnGG ↔ lnEQ
lnEQ ≠> lnGG	3.397	7.390**	0.010	

Note: ***, ** and * express significance at 1%, 5% and 10% level, respectively

5. Discussions

The findings indicate that environmental sustainability in emerging market economies exhibits a multidimensional structure simultaneously influenced by energy transition, digitalization, demographic change, and green development processes. The fact that the coefficients obtained from the AMG and FMOLS estimators produce largely similar results in terms of direction and statistical significance supports the reliability of the findings. In particular, the positive effects of renewable energy consumption, information and communication technologies, population aging, and green growth on the load capacity factor suggest that environmental quality is shaped not only by transformations in production structures but also by technological progress, demographic shifts, and sustainable growth policies. In contrast, the negative impact of industrialization on environmental quality may be considered an important consequence of the fact that industrial activities in emerging market economies still rely heavily on energy-intensive and carbon-dependent production processes.

The positive effect of renewable energy consumption on environmental quality can be explained by the ability of renewable energy utilization to reduce dependence on fossil fuels, limit carbon-intensive production processes, and contribute to the preservation of ecological capacity. The results obtained are consistent with the findings reported by Adebayo and Samour (2024) for the BRICS countries, Pata et al. (2023) for Germany, and Jahanger et al. (2024), who emphasize the importance of renewable energy investments for sustainable development. Similarly, the improvement in environmental quality associated with information and communication technologies may be attributed to the role of digital technologies in enhancing energy efficiency, optimizing resource utilization, and supporting the effectiveness of environmental management processes. This finding supports the results obtained by Dogan and Pata (2022) for the G7 countries and Mehmood et al. (2023) for the G8 economies.

One of the noteworthy findings of the study is that population aging emerges as the strongest determinant supporting environmental quality. The reduced participation of aging populations in energy-intensive production and consumption activities, their tendency to exhibit lower consumption patterns, and their relatively higher environmental awareness may be considered among the possible mechanisms explaining this result. This finding is similar to the evidence reported by Yang et al. (2021) for OECD countries, Yang et al. (2022b) for G7 countries, and Tarazkar et al. (2021) for Middle Eastern countries. Moreover, the identification of a bidirectional causal relationship between population aging and environmental quality suggests that the relationship between demographic transformation and environmental sustainability has a dynamic and mutually interactive nature.

The positive contribution of green growth to environmental quality indicates that economic growth can be achieved in a manner consistent with environmental sustainability objectives. The diffusion of low-carbon production processes, the promotion of environmental innovations, and improvements in resource efficiency may be considered the main explanatory mechanisms underlying the beneficial effect of green growth on environmental quality. In contrast, the negative effect of industrialization on the load capacity factor suggests that industrial policies in emerging market economies have not yet been adequately integrated with clean production technologies. This finding highlights the importance of addressing industrial transformation policies together with renewable energy investments, digitalization processes, and green growth strategies in order to ensure environmental sustainability.

6. Policy implications

The empirical findings of this study provide several policy implications for promoting environmental sustainability in emerging market economies. The results indicate that renewable energy consumption, information and communication technologies, population aging, and green growth improve environmental quality, whereas industrialization exerts adverse effects on environmental quality. In this regard, policymakers should develop comprehensive policy packages that support environmental sustainability.

The finding that industrialization reduces the load capacity factor suggests that industrial activities in emerging market economies still largely depend on energy-intensive and carbon-based production processes. Therefore, industrial policies should be more strongly integrated with clean production technologies. In particular, tightening emission standards in carbon-intensive sectors, implementing environmental taxes within the framework of the polluter-pays principle, and gradually reducing subsidies that encourage fossil fuel consumption may contribute to limiting environmental degradation. In addition, increasing investments in carbon capture, utilization, and storage technologies, promoting energy-efficient production processes, and encouraging firms to adopt certification systems in line with international environmental management standards may serve as important instruments for reducing the environmental costs associated with industrial activities.

The findings also demonstrate that renewable energy consumption is one of the key determinants improving environmental quality. This result points to the necessity of accelerating energy transition policies. Increasing public and private investments in renewable energy technologies, developing long-term financing mechanisms, deepening green bond markets, and strengthening incentive schemes for renewable energy projects would contribute to reducing dependence on fossil fuels. Moreover, modernizing energy infrastructures, adapting electricity grids to renewable energy sources, and expanding energy storage systems may constitute effective policy tools for enhancing the efficiency of the energy transition process.

The positive impact of information and communication technologies on environmental quality suggests that digitalization should be considered an important component of sustainable development policies. The widespread adoption of smart grids, smart transportation systems, big data analytics, Internet of Things applications, and digital supply chain management systems may contribute to optimizing energy consumption, reducing resource use in production processes, and improving environmental performance. Furthermore, supporting data centers with renewable energy sources and planning digital infrastructure investments in accordance with low-carbon development objectives are also of considerable importance.

One of the most notable findings of the study is that population aging emerges as the strongest determinant positively influencing environmental quality. This result suggests that demographic transformation processes should be integrated into environmental policymaking. Developing awareness programs aimed at encouraging environmentally friendly consumption habits among older individuals, promoting low-carbon lifestyles, and supporting sustainable healthcare, care, and social service policies tailored to the needs of aging populations may contribute to environmental sustainability. In addition, promoting environmentally friendly production practices in sectors producing goods and services for elderly populations may help harmonize demographic transformation with green development objectives.

Finally, the positive effect of green growth on environmental quality indicates that economic growth and environmental sustainability should not be viewed as competing objectives but rather as complementary goals. In this context, supporting environmental innovations, expanding green financing instruments, promoting energy efficiency investments, and effectively implementing environmental regulations may significantly contribute to achieving sustainable development goals in emerging market economies. Overall, improving environmental quality requires energy transition, digitalization, demographic change, and green growth policies to be considered as complementary components and implemented within the framework of a comprehensive sustainable development strategy.

7. Limitations and directions for future research

Although this study provides important findings regarding the determinants of environmental quality in emerging market economies, it has several limitations. The sample of the study is restricted to 19 emerging market economies due to data availability constraints. In particular, the fact that data on renewable energy consumption end in 2021 prevented the inclusion of more recent periods in the analysis. This situation limits, to some extent, the generalizability of the findings to all emerging market economies. Future studies may contribute to a more comprehensive assessment of whether the determinants of environmental quality differ according to economic structures and development levels by employing larger country samples and incorporating different country groups, such as developed economies, low-income countries, or high-emission economies.

Although the explanatory variables used in the study represent important determinants of environmental sustainability, other factors that may affect environmental quality, such as political uncertainty, green innovation, green finance, institutional quality, environmental regulations, financial development, and technological innovation, could not be incorporated into the model due to data limitations. Future studies may contribute to reducing omitted variable bias and obtaining stronger empirical evidence regarding the determinants of environmental sustainability by developing more comprehensive models that consider these variables.

Although the use of the load capacity factor as an indicator of environmental quality constitutes one of the important contributions of the study, future research may employ alternative environmental indicators, such as carbon emissions, ecological footprint, environmental performance indices, or adjusted net savings, to evaluate the extent to which the findings vary under different measures of environmental sustainability. In addition, the use of more advanced econometric approaches, including panel quantile regression methods, nonlinear panel models, threshold models, asymmetric estimators, or time-frequency techniques, may contribute to a more detailed understanding of the heterogeneous, nonlinear, and state-dependent relationships among the variables.

Declaration of competing interest

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

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Sustainable mobility futures: The roles of perceived value, attitude, and country-of-origin image in Chinese EV purchase intentions in Thailand

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HIGHLIGHTS

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ABSTRACT

Thailand has emerged as a major electric vehicle (EV) hub in Southeast Asia, with Chinese brands dominating over 70% of the market share in 2024. However, limited research has examined how Thai consumers perceive the multidimensional values of Chinese EVs and how these perceptions influence purchase intention. This study investigates the effects of functional, economic, and environmental values on consumer attitude and purchase intention toward Chinese EVs. Attitude is proposed as a mediator, while country-of-origin image serves as a moderator. A quantitative survey was conducted with 550 Thai consumers, and data were analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM). The results reveal that functional, economic, and environmental values have significant positive effects on attitude, which in turn strongly predicts purchase intention. Attitude fully mediates the relationships between all three perceived value dimensions and purchase intention. Additionally, country-of-origin image significantly moderates the relationships between perceived values and attitude. These findings contribute to the literature on perceived value and consumer behavior in emerging markets by integrating consumption values theory with the theory of planned behavior in the ASEAN context. Practical implications are provided for Chinese EV manufacturers and Thai policymakers to enhance sustainable EV adoption in Thailand.

1. Introduction

The global transition toward sustainable transportation has accelerated dramatically in recent years, driven by mounting concerns over climate change, air pollution, and energy security. In Southeast Asia, Thailand has positioned itself as the region's leading electric vehicle (EV) production and adoption hub. Through ambitious government initiatives such as the EV 3.0 and EV 3.5 policies, Thailand aims to achieve a 30% market share of zero-emission vehicles by 2030 (Board of Investment Thailand 2024). These policies have successfully attracted massive foreign investment, particularly from Chinese manufacturers.

Among the most prominent players are Chinese EV brands such as BYD, MG-SAIC, Great Wall Motor (GWM), Neta, and Changan. In 2024, Chinese manufacturers accounted for over 70% of Thailand's EV sales (MarkLines 2024; ASEAN Automotive Federation 2024). While these sales figures appear impressive, a notable gap exists between market penetration and genuine consumer acceptance.

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Many Thai consumers continue to hesitate when considering Chinese EVs, citing concerns over long-term reliability, resale value, brand image, after-sales service, and whether these vehicles truly align with Thai lifestyles and expectations.

This discrepancy highlights the need for deeper consumer behaviour research. Although EV adoption has received increasing academic attention, significant research gaps remain in the Thai context. Most existing studies in Thailand have focused predominantly on macrolevel factors such as government policy effectiveness, charging infrastructure development, range anxiety, and general barriers to EV adoption (Boonchunone et al. 2023). Some studies have examined consumer intention toward electric vehicles in general (Tissayakorn 2025; Boonkunone et al. 2023), yet they rarely distinguish between different country-of-origin brands.

Notably, very few studies have specifically examined Chinese-made EVs. Even fewer have adopted a multidimensional perceived value approach (functional, economic, and environmental values) to understand Thai consumers evaluations of these vehicles. Moreover, the critical mediating role of consumer attitude which bridges perceived value and purchase intention has been largely overlooked in the Thai setting. This omission is particularly important because Chinese brands carry unique socio-psychological connotations in Thailand, stemming from historical perceptions of Chinese products, trust issues, and strong preferences for Japanese and Korean brands. Such cultural and origin-related factors may significantly influence how consumers translate objective product advantages into positive attitudes and actual buying behaviour.

The lack of such context-specific research is surprising given the rapid market transformation. While international literature provides rich insights into EV adoption in Western and Chinese domestic markets (Rezvani et al. 2020; Hardman et al. 2018; Boonchunone et al. 2023; Ajzen's 1991), these findings may not fully transfer to emerging ASEAN economies where brand origin, collectivist culture, and policy-driven market changes create distinct consumer dynamics.

This study addresses a specific theoretical gap in the existing literature: although the relationships among perceived value, attitude, and purchase intention have been extensively studied in Western and East Asian EV markets, no prior study has simultaneously integrated Sheth et al.'s (1991) Theory of Consumption Values (TCV), Ajzen's (1991) Theory of Planned Behavior (TPB), and Fortwengel and Kostova (2023) practice-transfer framework to explain Chinese EV adoption in an ASEAN emerging market. The practice-transfer approach is specifically applied here to conceptualise the three value dimensions (functional, economic, environmental) as strategic practices that Chinese MNEs actively diffuse into the Thai market providing a mechanism-level explanation for why and how these values travel across borders and how host-country consumers accept or resist them. This integrative framework directly addresses the call for multi-framework, context-sensitive research in emerging ASEAN consumer markets. Specifically, this study seeks to answer three core research questions: (1) How do functional, economic, and environmental values directly influence Thai consumers' attitudes toward Chinese electric vehicles? (2) Does attitude significantly predict their purchase intention? and (3) Does attitude mediate the relationships between the three value dimensions and purchase intention?

To examine these questions, this study employed a quantitative survey of 550 Thai consumers and analysed the data using PLS-SEM, this study aims to provide both theoretical advancement and practical guidance. On the theoretical side, it extends the application of perceived value and TPB models to an under-researched cross-cultural, foreign-brand context in ASEAN markets. On the practical side, the findings will offer Chinese EV manufacturers (BYD, MG, GWM, etc.) clearer insights into which value dimensions matter most to Thai buyers, enabling them to refine marketing strategies, product positioning, and after-sales services. For Thai policymakers, the results will highlight effective levers to accelerate EV adoption and achieve the national 30% zero-emission vehicle target by 2030.

2. Theoretical background and hypothesis development

2.1. Theoretical background

Consumer decision-making for high-involvement products such as electric vehicles rarely rests on a single factor. It emerges from the interplay between what consumers perceive they will gain (perceived value) and how they evaluate the act of purchasing (attitude). To capture this process, the present study integrates two foundational frameworks: Sheth et al.'s (1991) Theory of Consumption Values (TCV) and Ajzen's (1991) Theory of Planned Behavior (TPB).

Following Fortwengel and Kostova (2023) practice-transfer framework, we treat the three core value dimensions functional, economic, and environmental as "organizational practices" that Chinese EV MNEs deliberately transfer across borders. In the Thai market, these values are not passive consumer perceptions, but strategic practices diffused through product features, marketing campaigns, community activities, and policy alignment.

Sheth et al. (1991) argue that consumers evaluate products along multiple value dimensions. Research on sustainable and technology-driven products has consistently shown that functional value (performance and quality), economic value (price and total cost of ownership), and environmental value (ecological benefit) stand out as especially powerful in the EV context (Sweeney and Soutar 2001; Schuitema et al. 2013; Han et al. 2017; Upadhyay and Kamble 2023).

TPB explains how these perceptions translate into action. According to Ajzen (1991), attitude is the most immediate predictor of behavioural intention. Previous studies have consistently reported relationships between perceived value, attitude, and behavioural intention in green consumption studies (Han et al. 2017; Upadhyay and Kamble 2023) and is particularly relevant in emerging markets where brand origin adds psychological complexity.

2.2. The influence of perceived values on attitude

Building on Sheth et al.'s (1991) Theory of Consumption Values and the PERVAL scale (Sweeney and Soutar 2001), this study focuses on three value dimensions that prior EV research has identified as particularly salient: functional, economic, and environmental. These dimensions are treated here not merely as consumer perceptions but as strategic practices that Chinese MNEs actively transfer to the Thai market through product design, pricing strategies, marketing messages, and sustainability positioning (Fortwengel and Kostova 2023). Each dimension is expected to shape Thai consumers' overall attitude toward Chinese EVs, though their relative influence may vary according to local economic conditions, infrastructure readiness, and environmental concerns.

2.2.1. Functional value

Functional value refers to the perceived utility derived from a product's objective performance characteristics, including driving range, acceleration, safety features, build quality, charging speed, and technological sophistication (Sheth et al. 1991; Sweeney and Soutar 2001). In the EV literature, functional value has repeatedly been shown to shape positive attitudes because consumers evaluate vehicles first and foremost on whether they "work well" in daily life (Han et al. 2017). For Thai buyers, who often navigate long commutes in congested Bangkok traffic or occasional upcountry trips on less-developed roads, reassurance about real-world range, charging convenience, and overall reliability is especially salient. When these practical attributes meet or exceed expectations, consumers are more likely to form a favourable attitude toward the vehicle and the brand behind it.

H1. Functional value positively influences Thai consumers' attitude toward Chinese electric vehicles.

2.2.2. Economic value

Economic value (also labelled functional value price in the PERVAL scale) captures the monetary and non-monetary trade-offs consumers make, including purchase price, electricity versus gasoline costs, maintenance expenses, resale value, and the impact of government subsidies (Zeithaml 1988; Sweeney and Soutar 2001). In price sensitive emerging markets like Thailand, where Chinese EVs are positioned as affordable alternatives to more established Japanese and Korean models, economic value frequently emerges as the dominant driver of attitude (Sierzchula et al. 2014; Boonchunone et al. 2023). Thai consumers who perceive a favourable total cost of ownership reinforced by current subsidies and lower operating costs are more likely to develop a positive overall evaluation of Chinese EVs. This dimension is particularly powerful in a market where many buyers are first-time EV adopters and must carefully weigh immediate financial outlays against long-term savings.

H2. Economic value positively influences Thai consumers' attitude toward Chinese electric vehicles.

2.2.3. Environmental value

Environmental value reflects the extent to which consumers believe that purchasing and using an EV contributes to ecological sustainability, reduces carbon emissions, and improves local air quality (Hartmann and Apaolaza-Ibáñez 2012; Schuitema et al. 2013). In Thailand, where seasonal PM2.5 episodes in major cities have dramatically heightened public awareness of air pollution, this value dimension carries growing weight. Consumers who feel that driving a Chinese EV aligns with their personal and societal responsibility to protect the environment tend to form more favourable attitudes. Beyond self-interest, this dimension taps into broader moral and collective concerns that are increasingly prominent in emerging-market consumer behaviour.

H3. Environmental value positively influences Thai consumers' attitude toward Chinese electric vehicles**.**

2.3. Attitude toward intention

Attitude occupies a central position in consumer behaviour research, particularly for high-involvement purchases such as automobiles. Following Ajzen's (1991) Theory of Planned Behavior (TPB), attitude is conceptualised as an individual's overall favourable or unfavourable evaluation of performing a specific behaviour in this case, purchasing a Chinese electric vehicle. It reflects not only cognitive beliefs about the product's attributes but also affective feelings and behavioural tendencies that together shape a consumer's readiness to act.

In the context of car buying, attitude has consistently emerged as the strongest and most proximal predictor of purchase intention across numerous studies (Armitage and Conner 2001; Han et al. 2017; Upadhyay and Kamble 2023). When consumers perceive the act of buying as "good", "desirable", "wise", or "pleasant", their intention to follow through increases substantially. Conversely, even strong perceived benefits can fail to translate into action if the overall evaluation remains lukewarm or negative. This is especially relevant for Chinese EVs in Thailand, where lingering scepticism about brand origin, after-sales service, and long-term reliability can temper otherwise favourable perceptions of price and technology.

The importance of attitude becomes even clearer when viewed through the lens of practice transfer in multinational enterprises (Fortwengel and Kostova 2023). Chinese EV manufacturers are not merely selling vehicles; they are transferring a bundle of practices functional performance standards, economic value propositions, and environmental claims across borders. Thai consumers' attitudes represent the psychological filter through which these transferred practices are accepted, adapted, or resisted. A favourable attitude signals successful internalisation of these practices, while a weak attitude may indicate partial adoption or outright rejection. Therefore, understanding how attitude links perceived values to intention is essential for explaining both the successes and the remaining gaps in Chinese EV adoption in Thailand.

H4. Attitude positively influences the purchase intention of Chinese EVs among Thai consumers.

2.3.1. Country-of-origin effect

The country-of-origin (COO) effect plays an important role in shaping consumer evaluations of foreign products, especially in emerging markets where consumers rely on country image as a cue for quality, reliability, and innovation (Bilkey and Nes 1982; Han 1989). In the Thai EV market, Chinese electric vehicles face mixed perceptions because Thai consumers traditionally trust Japanese and Korean automotive brands more strongly. Although Chinese EV manufacturers such as BYD have improved technology and expanded local production in Thailand, concerns regarding long-term reliability, after-sales service, and resale value still influence consumer attitudes (Boonchunone et al. 2023).

The COO effect interacts with consumers' perceived functional, economic, and environmental values rather than replacing them. A favourable image of Chinese products can strengthen positive attitudes toward EVs, while a negative image may weaken the impact of these value perceptions by creating uncertainty and scepticism. Consistent with practice-transfer theory (Fortwengel and Kostova 2023), the success of transferring foreign products into a local market depends not only on product quality but also on the perceived credibility of the originating country. Therefore, this study considers COO image as a moderating variable influencing the relationship between perceived value dimensions and consumer attitudes toward Chinese EVs in Thailand.

H5a. Country-of-origin image moderates the relationship between functional value and Thai consumers' attitude toward Chinese electric vehicles, such that the positive effect is stronger when the COO image is more favourable.

H5b. Country-of-origin image moderates the relationship between economic value and Thai consumers' attitude toward Chinese electric vehicles, such that the positive effect is stronger when the COO image is more favourable.

H5c. Country-of-origin image moderates the relationship between environmental value and Thai consumers' attitude toward Chinese electric vehicles, such that the positive effect is stronger when the COO image is more favourable.

2.4. Mediating role of attitude

Although the three value dimensions can exert direct effects on purchase intention, the TPB framework and numerous empirical studies in the EV domain suggest that their influence is largely transmitted through attitude (Moons and De Pelsmacker 2012; Han et al. 2017; Upadhyay and Kamble 2023). In other words, functional features, cost savings, and environmental benefits matter because they first create a positive evaluation of the product in the consumer's mind; only then does that evaluation translate into a concrete buying intention. This mediation pathway is theoretically grounded in the idea that values provide the cognitive and affective foundation for attitude formation, while attitude serves as the immediate psychological precursor to intention.

Mediation analyses in similar EV studies have confirmed full or partial mediation in the majority of cases (Noppers et al. 2015; Kang and Moreno 2020). In the Thai context, where Chinese EVs must overcome both functional scepticism and brand-origin concerns, attitude is expected to play an especially critical bridging role. Without a favourable overall evaluation, even strong perceptions of economic or environmental benefits may fail to convert into purchase intention. By testing these mediation effects, the present study not only validates the classic value-attitude-intention sequence but also contributes to the broader practice-transfer literature by showing how transferred value practices are psychologically processed and internalised by consumers in an emerging ASEAN market.

Consequently, the following mediation hypotheses are proposed:

H6a. Attitude mediates the relationship between functional value and purchase intention toward Chinese EVs.

H6b. Attitude mediates the relationship between economic value and purchase intention toward Chinese EVs.

H6c. Attitude mediates the relationship between environmental value and purchase intention toward Chinese EVs.

The conceptual research model framework of this study is presented in detail in Figure 1.

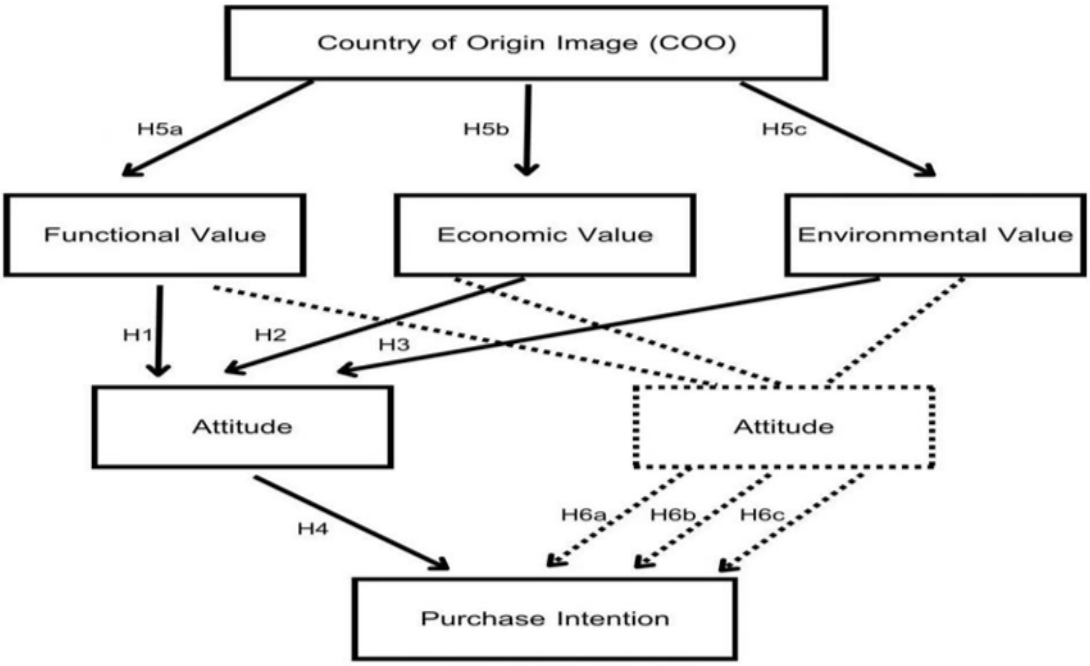

Figure 1. Conceptual research model

3. Materials and methods

3.1. Measures and questionnaire development

All constructs in this study were measured using previously validated multi-item scales adapted from prior literature. Functional value and economic value were adapted from Sweeney and Soutar (2001), environmental value from Schuitema et al. (2013), country-of-origin image from Verlegh and Steenkamp (1999), attitude from Ajzen (1991), and purchase intention from Han et al. (2017). All measurement items were modified to fit the context of Chinese electric vehicles in Thailand while preserving the conceptual meaning of the original scales. Ethical approval for this questionnaire-based study was obtained from Hubei University of Technology prior to data collection.

The questionnaire was initially developed in English and subsequently translated into Thai using a back-translation procedure to ensure linguistic equivalence and content accuracy. To enhance content validity, the questionnaire was reviewed by three experts in consumer behaviour and marketing research, including two university lecturers and one researcher with experience in EV-related studies. Minor wording revisions were made based on their feedback to improve clarity and contextual relevance.

Table 1. Measurement scales and sources

Construct	Number of items	Original source	Adapted focus in this study
Functional Value	4	Sweeney and Soutar (2001)	Performance, reliability, safety, and charging speed of Chinese EVs
Economic Value	4	Sweeney and Soutar (2001)	Purchase price, operating cost, maintenance, resale value, and subsidies
Environmental Value	4	Schuitema et al. (2013)	Contribution to reducing air pollution and carbon emissions
Country-of-Origin Image	5	Verlegh and Steenkamp (1999)	Perceptions toward "Made in China" automobiles
Attitude	6	Ajzen (1991)	Overall evaluation toward purchasing a Chinese EV
Purchase Intention	4	Han et al. (2017)	Intention to buy within 12 months and preference over other brand

Prior to the main survey, a pilot test was conducted with 30 Thai respondents who were familiar with electric vehicles. The pilot study aimed to evaluate item clarity, questionnaire flow, and preliminary reliability. The results indicated acceptable internal consistency across all constructs, with Cronbach's alpha values exceeding the recommended threshold of 0.70. Several items were slightly revised to improve readability before the final data collection process. All items were measured using a five-point Likert scale ranging from 1 ("strongly disagree") to 5 ("strongly agree"). The details of each construct are presented in Table 1.

3.2. Research design and data collection

This study employed a cross-sectional survey design to investigate the relationships among perceived values, attitude, country-of-origin image, and purchase intention toward Chinese electric vehicles among Thai consumers. Data were collected between January and May 2026 through both online and offline channels.

A purposive sampling approach was adopted to target individuals aged 18 years and above who were either current EV users or potential EV buyers the population most relevant to examining purchase intention toward Chinese EVs. Respondents were recruited through EV related Facebook groups, online automotive communities, EV exhibitions, shopping malls, charging station areas, and university networks across all major regions of Thailand. Snowball sampling was additionally employed to reach respondents who could not be accessed through these channels. While purposive and snowball sampling do not guarantee full statistical representativeness, the diversity of recruitment channels combined with geographic spread across all six regions of Thailand (Table 2) ensures reasonable coverage of Thai EV-interested consumers. We acknowledge this as a potential limitation and encourage future research to employ random sampling to improve generalisability. Although the sample is skewed toward urban, higher-educated respondents, this profile is consistent with the documented characteristics of early EV adopters in emerging markets (Rogers 2003; Boonchunone et al. 2023) a group particularly relevant for studying purchase intentions toward a new technology category. Future studies should nonetheless employ probability-based random or stratified sampling to improve representativeness across income groups and geographic regions.

A total of 612 responses were initially collected. After screening for incomplete questionnaires, straight-lining patterns, and inconsistent responses, 550 valid responses remained for analysis. The final sample size exceeded the minimum requirement recommended for PLS-SEM analysis and was considered adequate for statistical testing.

3.3. Common method bias and data quality

To minimise the potential for common method bias (CMB), this study applied both procedural and statistical remedies. Procedurally, respondent anonymity was ensured, different scale anchors were used for independent and dependent variables, and questionnaire items were organised into clearly separated sections to reduce response pattern bias (Jordan and Troth 2020; Fuller et al. 2016). Statistically, Harman's single-factor test was applied as a preliminary screen, with the first factor explaining only 38.4% of the total variance below the recommended 50% threshold. A full collinearity VIF assessment (Kock 2015) showed all VIF values below 3.3 (range: 1.62-2.87). We acknowledge that Podsakoff et al. (2012) recommend the marker variable technique as the most rigorous CMB control. While the marker variable technique is ideal, our multi-remedy approach (procedural controls + Harman's test + full collinearity VIF + unmeasured latent factor check) substantially mitigates CMB concerns; the latent factor test confirmed path coefficient changes of less than 0.05 across all paths well within acceptable bounds (Hair et al. 2022). Future studies should incorporate a dedicated marker variable or longitudinal design for more definitive CMB control.

Prior to finalising the questionnaire, the researchers conducted showroom visits and test drives of three leading Chinese EV models available in Thailand (BYD Atto 3, MG4 EV, GWM Ora Good Cat) to inform functional value item refinement. These activities ensured that scale items captured attributes most salient to Thai consumers including driving range, build quality, ADAS features, and charging convenience rather than relying solely on abstract constructs from prior literature. These activities did not constitute primary data collection and are reported here solely as part of the questionnaire development and content validity process; all study findings are based entirely on the quantitative survey data from 550 respondents analysed through PLS-SEM.

3.4. Analytical approach

The data were analysed using Partial Least Squares Structural Equation Modelling (PLS-SEM) with SmartPLS 4 software. The choice of PLS-SEM over covariance-based SEM (CB-SEM) was deliberate and based on several considerations. First, PLS-SEM is the preferred approach when the primary objective is prediction and the explanation of variance in endogenous constructs, rather than model fit confirmation which is the orientation of this study (Hair et al. 2019; Ringle et al. 2020). Second, PLS-SEM performs well with complex models involving multiple mediating and moderating relationships simultaneously, such as the current model featuring three indirect paths and three COO interaction terms (Hair et al. 2022). Third, PLS-SEM does not require multivariate normality assumptions, which is important given the use of Likert-scaled survey data. CB-SEM would be less suitable due to the model's complexity and our focus on prediction rather than theory confirmation (Hair et al. 2019; Ringle et al. 2020). CB-SEM is optimised for confirmatory testing via global fit indices (CFI, RMSEA, SRMR) and assumes multivariate normality neither of which aligns with the present study's design. These distinctions collectively justify PLS-SEM as the more appropriate analytical choice.

The analysis followed a two-step procedure. First, the measurement model was evaluated to assess reliability and validity. Internal consistency reliability was examined using Cronbach's alpha and composite reliability (CR). Convergent validity was assessed through factor loadings and average variance extracted (AVE), while discriminant validity was evaluated using the heterotrait-monotrait (HTMT) ratio.

Second, the structural model was assessed to test the proposed hypotheses. Bootstrapping with 5,000 resamples was conducted to examine the significance of path coefficients, mediation effects, and moderation effects. In addition, the coefficient of determination (R^2), effect size (f^2), and predictive relevance (Q^2) were evaluated to determine the explanatory and predictive power of the model.

Prior to hypothesis testing, data screening procedures were performed to identify missing values, outliers, and multicollinearity issues. No severe multicollinearity was detected, as all variance inflation factor (VIF) values were below the recommended threshold. The data were therefore considered suitable for subsequent SEM analysis.

4. Results

4.1. Demographic profile of respondents

A total of 550 valid responses were retained for analysis. Table 2 presents the demographic characteristics of the sample. The respondents were relatively balanced by gender (52% male, 48% female). The majority were aged between 24 and 39 years (60%), held at least a bachelor's degree (78%), and reported monthly incomes between 20,001 and 60,000 THB (61%). Geographically, 44% resided in the Central Region, consistent with the concentration of EV markets in and around Bangkok and its vicinity. Notably, 62% of respondents did not yet own an EV but expressed interest in purchasing one, while 10% already owned a Chinese-brand EV. This profile indicates that the sample comprised both current users and potential adopters, which is appropriate for examining purchase intention.

Table 2. Demographic profile of respondents (N = 550)

Characteristic	Category	Frequency	Percentage
Gender	Male	286	52.00%
	Female	264	48.00%
Age	18–23 years	110	20.00%
	24–29 years	165	30.00%
	30–39 years	165	30.00%
	40–49 years	83	15.00%
	50 years and above	27	5.00%
Education	Below bachelor's	121	22.00%
	Bachelor's degree	319	58.00%
	Above bachelor's	110	20.00%
Monthly income (THB)	< 20,000	154	28.00%
	20,001–40,000	198	36.00%
	40,001–60,000	138	25.00%
	> 60,000	60	11.00%
Residence	Central Region	242	44.00%
	Northeastern Region	94	17.00%
	Western Region	77	14.00%
	Northern Region	55	10.00%
	Southern Region	50	9.00%
	Eastern Region	32	6.00%
EV ownership / interest	No ownership but interested	341	62.00%
	Not interested	154	28.00%
	Own Chinese EV	55	10.00%

4.2. Descriptive statistics

All constructs were measured on a 5-point Likert scale (1 = strongly disagree to 5 = strongly agree). As shown in Table 3, respondents generally held positive perceptions toward Chinese EVs. Environmental value and attitude recorded the highest mean scores (M = 3.90), followed by economic value (M = 3.84). Functional value received the lowest mean score among the main constructs (M = 3.62), suggesting that Thai consumers still have some reservations regarding the performance and quality aspects of Chinese EVs compared to other value dimensions.

Table 3. Descriptive statistics of key constructs (N = 550)

Construct	Mean	SD	Interpretation
Environmental Value	3.9	0.68	High
Attitude	3.9	0.71	High
Economic Value	3.84	0.65	High
Purchase Intention	3.75	0.74	Moderate-High
Functional Value	3.62	0.69	Moderate

4.3. Measurement model assessment

Prior to testing the structural model, the measurement model was evaluated for reliability and validity. All constructs demonstrated strong internal consistency, with Cronbach's α values ranging from 0.81 to 0.89 and composite reliability (CR) values ranging from 0.86 to 0.92, all exceeding the recommended thresholds of 0.70 and 0.80 respectively (Hair et al. 2022). Convergent validity was confirmed as average variance extracted (AVE) for all constructs ranged from 0.52 to 0.67, exceeding the 0.50 threshold (Fornell and Larcker 1981). All indicator loadings exceeded 0.70. Discriminant validity was established using the HTMT ratio, with all values below 0.85 (highest HTMT = 0.79, between environmental value and attitude), confirming construct distinctiveness (Henseler et al. 2015). Full item loadings, Cronbach's α, CR, AVE, and the HTMT matrix are reported in Table 4. These results indicate that the measurement model is reliable and valid for subsequent structural analysis.

Table 4. Measurement model: Reliability, validity, and discriminant validity
Part A. Construct reliability and convergent validity

Construct	Items	Loading Range	α	CR	AVE
Functional Value	4	0.71–0.83	0.81	0.87	0.53
Economic Value	4	0.74–0.86	0.84	0.89	0.58
Environmental Value	4	0.78–0.89	0.88	0.92	0.67
Country-of-Origin Image	5	0.72–0.84	0.86	0.90	0.55
Attitude	6	0.75–0.88	0.89	0.91	0.63
Purchase Intention	4	0.73–0.85	0.83	0.88	0.52

Note: α = Cronbach's alpha; CR = Composite Reliability; AVE = Average Variance Extracted. All values meet recommended thresholds (α > 0.70; CR > 0.80; AVE > 0.50).

Part B. HTMT discriminant validity matrix

	FV	EV	ENV	COO	ATT	PI
FV	-					
EV	0.61	-				
ENV	0.55	0.63	-			
COO	0.52	0.58	0.60	-		
ATT	0.68	0.72	0.79	0.64	-	
PI	0.59	0.65	0.70	0.57	0.74	-

Note: FV = Functional Value; EV = Economic Value; ENV = Environmental Value; COO = Country-of-Origin Image; ATT = Attitude; PI = Purchase Intention. All HTMT values < 0.85, confirming discriminant validity (Henseler et al. 2015). Threshold = 0.85.

4.4. Structural model results

The structural model was examined using Partial Least Squares Structural Equation Modelling (PLS-SEM) with SmartPLS 4. Bootstrapping with 5,000 resamples was performed to test the significance of path coefficients. The model demonstrated satisfactory explanatory power, with $R^2 = 0.58$ for attitude and $R^2 = 0.45$ for purchase intention both exceeding the $R^2 \geq 0.26$ threshold for substantial explanatory power (Cohen 1988). Predictive relevance was confirmed via blindfolding analysis: $Q^2 = 0.34$ for attitude and $Q^2 = 0.21$ for purchase intention (both well above 0), indicating meaningful out-of-sample predictive accuracy (Geisser 1974; Stone 1974). Effect sizes (f^2) were assessed for each path: environmental value ($f^2 = 0.23$, medium effect), economic value ($f^2 = 0.12$, small-to-medium), functional value ($f^2 = 0.05$, small), and attitude to purchase intention ($f^2 = 0.45$, large). These patterns indicate that while all paths are statistically significant, practical significance varies considerably across value dimensions a distinction important for managerial prioritisation.

4.4.1. Direct effects

As shown in Table 5, environmental value was the strongest predictor of attitude ($\beta = 0.42$), followed by economic value ($\beta = 0.31$) and functional value ($\beta = 0.19$). Attitude had a strong positive effect on purchase intention ($\beta = 0.67$).

Table 5. Presents the results of the direct relationships in the structural model

Hypothesis	Path	β	t-value	p-value	Decision	f²
H1	Functional Value → Attitude	0.19	3.85	< 0.01	Supported	0.05
H2	Economic Value → Attitude	0.31	6.12	< 0.001	Supported	0.12
H3	Environmental Value → Attitude	0.42	8.47	< 0.001	Supported	0.23
H4	Attitude → Purchase Intention	0.67	14.92	< 0.001	Supported	0.45

Note: β = standardized path coefficient; f² = effect size (0.02 = small, 0.15 = medium, 0.35 = large)

4.4.2. Mediation analysis

Reports the mediation effects of attitude on the relationship between perceived values and purchase intention. The results confirm that attitude significantly mediates the relationships between all three perceived value dimensions and purchase intention. Environmental value showed the strongest indirect effect in Table 6.

Table 6. Results of mediation analysis (indirect effects)

Hypothesis	Indirect Path	Indirect β	t-value	p-value	Decision
H6a	Functional Value → Attitude → Purchase Intention	0.13	3.72	< 0.01	Supported
H6b	Economic Value → Attitude → Purchase Intention	0.21	5.68	< 0.001	Supported
H6c	Environmental Value → Attitude → Purchase Intention	0.28	7.95	< 0.001	Supported

4.4.3. Moderation analysis (Country-of-origin image)

The moderation analysis revealed that Country-of-Origin (COO) image significantly strengthens the positive relationships between all three value dimensions and attitude, with the strongest moderating effect on the functional value-attitude relationship. These results are presented in Table 7.

Table 7. Results of moderation effects

Hypothesis	Indirect Path	Indirect β	t-value	p-value	Decision
H5a	Functional Value × COO → Attitude	0.14	2.91	< 0.01	Supported
H5b	Economic Value × COO → Attitude	0.12	2.45	< 0.05	Supported
H5c	Environmental Value × COO → Attitude	0.09	2.08	< 0.05	Supported

5. Discussion

5.1. Key findings

The structural model results reveal several important findings. Environmental value emerged as the strongest predictor of Thai consumers' attitude toward Chinese electric vehicles ($\beta = 0.42$, $p < 0.001$), followed by economic value ($\beta = 0.31$, $p < 0.001$) and functional value ($\beta = 0.19$, $p < 0.01$). Attitude was found to be a strong predictor of purchase intention ($\beta = 0.67$, $p < 0.001$). The mediation analysis confirmed that attitude fully mediates the relationships between perceived values and purchase intention for most paths, with indirect effects of 0.28 (environmental), 0.21 (economic), and 0.13 (functional). Additionally, country-of-origin image significantly moderated the relationships between all three value dimensions and attitude. The model explained 58% of the variance in attitude and 45% of the variance in purchase intention.

5.2. Discussion

The finding that environmental value is the strongest predictor of attitude (β = 0.42) warrants contextual interpretation beyond simple alignment with prior literature. In the Thai context, this result likely reflects two converging forces: the rapid escalation of PM2.5 related health crises in Bangkok and major cities since 2019, and the Thai government's high-profile EV 3.0 and EV 3.5 policy packages, which have explicitly framed EV adoption as an environmental imperative (Board of Investment Thailand 2024). This institutional framing appears to have elevated environmental motivation to a primary evaluative criterion. Although previous Thai studies have also reported that perceived value significantly influences EV adoption, the relative importance of individual value dimensions appears to vary across studies (Boonchunone et al. 2023) that identified economic factors as the dominant driver, suggesting a shift over time. This pattern is consistent with longitudinal trends observed in Chinese domestic EV studies (Han et al. 2017) and European markets (Noppers et al. 2015), but notable in its speed of emergence in a developing ASEAN economy. It also signals that Chinese EV brands' investment in green branding is finding resonance with Thai consumers a positive outcome of the practice-transfer strategy identified in this study.

Economic value remains the second strongest driver (β = 0.31), confirming that Thai consumers are highly sensitive to price, total cost of ownership, and government incentives consistent with findings from other price-sensitive emerging markets (Sierzchula et al. 2014). The relatively weaker effect of functional value (β = 0.19, f^2 = 0.05) demands a more nuanced explanation than simple quality concerns. Thailand has been dominated by Japanese automotive brands (Toyota, Honda, Isuzu) for over four decades; these brands have built deep trust through extensive dealer networks and consistent reliability track records. Chinese EV brands are evaluated against this entrenched benchmark, resulting in a "credibility discount": even when functional attributes are objectively competitive, consumers apply greater scepticism to Chinese brands' real-world durability and after-sales support. This is consistent with country-of-origin research suggesting that consumers often rely on product origin as an indicator of quality when evaluating unfamiliar brands (Bilkey and Nes 1982; Verlegh and Steenkamp 1999) finding that brand familiarity moderates how functional cues translate into product evaluation. Importantly, the small effect size for functional value (f^2 = 0.05) implies that further improvements in technical specifications alone are unlikely to significantly move Thai consumer attitudes a finding with direct strategic implications discussed in Section 5.3.2. By contrast, the large effect of attitude on purchase intention (f^2 = 0.45) and the medium effect of environmental value (f^2 = 0.23) confirm that these pathways are not only statistically significant but also practically meaningful, reinforcing the priority that manufacturers and policymakers should assign to environmental value communication and attitude-building over functional feature promotion alone.

This result indicates that attitude is a key mechanism linking perceived values and purchase intention. Specifically Thai consumers do not buy Chinese EVs merely because they are cheap or environmentally friendly. Rather, these attributes must first create a positive overall evaluation (attitude) before translating into actual purchase intention. This finding supports the integration of Sheth et al.'s (1991) Theory of Consumption Values and Ajzen's (1991) Theory of Planned Behavior in the Thai context. The significant moderating role of country-of-origin image further highlights that negative historical perceptions of Chinese products still influence consumer judgment, especially for high-involvement products such as automobiles. Even when consumers perceive high value in the vehicles, a favourable country image can strengthen, while an unfavourable one can weaken, the formation of positive attitudes.

5.3. Implications

5.3.1. Theoretical implications

This study makes three distinct theoretical contributions to the existing literature. First, it addresses a gap by providing the first empirical test of an integrated TCV-TPB-practice-transfer model for

Chinese-brand EVs in an ASEAN emerging market. While prior studies have applied TCV (Han et al. 2017; Upadhyay and Kamble 2023) or TPB (Han et al. 2017) separately to EV adoption, none has synthesised these frameworks with Fortwengel and Kostova (2023) practice-transfer lens. This integration reveals not only what consumers value, but the mechanism by which Chinese manufacturers' strategic practices are psychologically internalised in a host market. Second, the finding that attitude fully mediates all three value intention relationships stronger than the partial mediation found in many prior studies (Moons and De Pelsmacker 2012; Kang and Moreno 2020) suggests that in markets with strong incumbent brands and brand-origin scepticism, attitude plays an especially critical filtering role, extending the value-attitude-intention framework to cross-cultural, challenger-brand scenarios. Third, confirmation of COO image as a boundary condition adds a moderating layer to existing practice-transfer theory, showing that brand-country image affects the effectiveness of value communication itself.

Second, by demonstrating the significant moderating role of country-of-origin image, the study advances the understanding of how psychological and socio-cultural factors interact with consumer value perceptions. This is particularly relevant in markets where brand origin continues to influence product evaluation despite objective product improvements. Finally, the research contributes to practice-transfer theory (Fortwengel and Kostova 2023) by illustrating how strategic value propositions offered by Chinese multinational enterprises are perceived, filtered, and internalized by consumers in a host country context.

5.3.2. Practical implications

The findings provide practical implications for EV manufacturers and policymakers. For Chinese EV manufacturers (e.g., BYD, MG, and Great Wall Motor), the results highlight the need to prioritize environmental value in marketing communications, as it exerts the strongest influence on Thai consumers' attitudes. Campaigns that clearly demonstrate real-world environmental benefits and alignment with Thailand's sustainability goals could be highly effective.

Although economic value remains important, manufacturers should not rely solely on price competition. Instead, greater emphasis must be placed on strengthening functional value perceptions through improved product quality, reliability, after-sales service, and transparent communication regarding long-term performance. Efforts to enhance country-of-origin image such as highlighting local manufacturing, technology partnerships with established global suppliers, and quality certifications are also recommended to amplify the positive effects of all value dimensions.

For Thai policymakers and related agencies, the empirical findings suggest several concrete policy interventions directly linked to this study's results. The strong environmental value effect ($\beta = 0.42$) indicates that policy communication should explicitly connect EV adoption with measurable pollution reductions for example, quantifying that replacing one conventional vehicle with a Chinese EV reduces annual CO_2 emissions by approximately 2.5 tonnes under Thailand's current energy mix. Given that PM2.5 crises are seasonal, the Department of Land Transport could consider time-limited EV incentives during high-pollution periods to capitalise on heightened environmental salience. The weaker functional value effect further suggests that consumer confidence in Chinese EV reliability could be bolstered through third-party quality certification or government-mandated warranty extension requirements for Chinese brands directly addressing the credibility discount identified in this study. Finally, given the COO moderation finding, initiatives that increase visibility of Chinese EV local manufacturing (e.g., BYD's Rayong plant) would strengthen country-of-origin image and amplify attitudinal effects of all three value dimensions, supporting the 30% zero-emission vehicle target by 2030.

5.4. Conclusion

The findings suggest that environmental value is the most influential factor shaping Thai consumers' attitudes toward Chinese electric vehicles. One possible explanation is the increasing public concern over environmental problems in Thailand, particularly PM2.5 air pollution in Bangkok and other urban areas. In recent years, air pollution has received extensive media coverage and public attention, leading many consumers to become more aware of environmentally friendly transportation alternatives. As a result, electric vehicles are increasingly viewed not only as a modern technology but also as a practical solution to environmental and health concerns. This finding is consistent with prior studies indicating that environmental awareness positively influences green consumption behaviour in emerging markets.

Economic value also showed a significant positive effect on attitude, reflecting the price-sensitive nature of Thai consumers. Compared with Japanese and European EV brands, Chinese EV manufacturers have positioned themselves competitively through lower prices, attractive features, and government subsidy eligibility. For many consumers, lower operating costs and reduced fuel expenses make Chinese EVs financially attractive. This result supports previous research suggesting that perceived economic benefits remain an important driver of EV adoption in developing economies where purchasing power varies substantially across consumers.

In contrast, functional value showed the weakest effect among the three value dimensions. Although Chinese EV brands such as BYD, MG, and GWM offer advanced technologies and modern vehicle features, some Thai consumers may still have concerns regarding long-term durability, battery reliability, after-sales service quality, and resale value. These concerns may be influenced by Thailand's long-standing familiarity with Japanese automotive brands, which have established strong reputations for reliability and service networks over several decades. Consequently, even though Chinese EVs are technologically competitive, some consumers may remain cautious when evaluating product quality and long-term ownership experience.

The strong positive relationship between attitude and purchase intention indicates that consumers overall evaluations of Chinese EVs play an important role in shaping future purchasing decisions. The mediation results further suggest that perceived values influence purchase intention indirectly through attitude formation. In other words, consumers are unlikely to purchase Chinese EVs based solely on economic or environmental benefits unless these perceptions first contribute to a favourable overall attitude toward the vehicles. This finding supports prior studies applying the Theory of Planned Behavior in sustainable consumption contexts.

The moderation effects of country-of-origin image also provide important insights into Thai consumer behaviour. Although Chinese manufacturers have significantly improved their technological capabilities and market presence in Thailand, perceptions associated with "Made in China" products continue to influence consumer evaluations. A favourable country image appears to strengthen the positive effects of perceived value on attitude, whereas scepticism toward Chinese products may weaken these relationships. This finding reflects the continuing importance of country-of-origin perceptions in high-involvement purchases such as automobiles, particularly in emerging markets where consumers often rely on brand origin as a signal of product quality and trustworthiness.

5.5. Limitations and future research directions

Despite its contributions, this study has several limitations that should be acknowledged. First, the cross-sectional survey design captures consumer perceptions at a single point in time, making it impossible to establish causal directionality or track changes in attitudes and purchase intentions as the Thai EV market matures. Given the rapid pace of market evolution with new Chinese EV models entering Thailand nearly every quarter longitudinal research would be valuable for capturing how perceived value dimensions and their relative importance shift over time.

Second, this study employed purposive and snowball sampling, which limits the statistical generalisability of the findings to the broader Thai population. Respondents were disproportionately drawn from urban areas (44% Central Region) and skewed toward higher education levels (78% bachelor's degree or above), which may not fully represent the diversity of potential EV adopters in semi-urban and rural Thailand. Future studies should consider probability based random sampling or stratified sampling to improve external validity.

Third, despite the application of multiple procedural and statistical controls, the possibility of common method bias inherent in single source, self reported survey data cannot be entirely eliminated. Future research could address this through split sample designs, time lagged surveys, or the incorporation of objective behavioural data (e.g., actual EV purchase records) to validate self-reported purchase intentions.

Fourth, this study focuses exclusively on Thailand as a single-country context. While Thailand is the most advanced EV market in ASEAN, consumer perceptions of Chinese EVs may differ substantially in other emerging markets such as Indonesia, Vietnam, Malaysia, and the Philippines, where institutional environments, cultural attitudes toward Chinese products, and government EV policies vary. Cross-national comparative studies would contribute significantly to the generalisability and theoretical development of practice-transfer frameworks in the ASEAN context.

Fifth, the study examined three value dimensions (functional, economic, environmental) drawn from the TCV framework. Future research could explore additional value dimensions such as social value (prestige and peer influence), emotional value (driving enjoyment and brand attachment), and conditional value (context-specific use cases) to develop a more comprehensive understanding of Chinese EV evaluation. Additionally, integrating technology acceptance variables (e.g., perceived ease of use, charging infrastructure adequacy) alongside perceived value constructs may yield richer explanatory models.

Finally, future research should investigate how the rapid expansion of Chinese EV manufacturers' local operations in Thailand (e.g., BYD's Rayong manufacturing facility) influences country-of-origin perceptions over time. As "Made in Thailand" Chinese EVs become more prevalent, the traditional COO effect may diminish, potentially altering the moderating dynamics identified in this study. Longitudinal research tracking COO perception changes alongside market development would be a particularly valuable contribution to both practice-transfer theory and EV adoption literature.

Declaration of competing interest

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

Ethical approval

Regarding the conduct of this research, an "Ethics Permission Certificate" dated 05/01/2026 and numbered 12 was obtained from the Ethics Committee of the Hubei University of Technology.

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The views expressed in this study are those of the author.

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Digitalization and sustainability in corporate reporting: Evidence from an emerging market

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HIGHLIGHTS

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ABSTRACT

This study examines how the discourse on digitalisation and sustainability in the annual reports of BIST100 companies evolved between 2015 and 2024, and what this change implies in terms of corporate reporting priorities. Using text mining and natural language processing techniques, the annual reports were analysed through lexicon-based topic measurement, trend and structural break tests, TF-IDF and LDA-based topic modelling, and sustainability sub-theme analysis. The findings indicate that financial and governance themes have retained their central position; however, transformation-focused non-financial themes such as digitalisation and sustainability are becoming increasingly prominent. Sustainability showed an increase of 501.5 per cent, whilst digitalisation increased by 276.6 per cent; a structural break was identified for both themes in 2019. The LDA results reveal that these two themes are increasingly converging under a common 'Digital and Sustainable Transformation' umbrella. Furthermore, it is observed that the sustainability discourse is shifting from a focus on social responsibility towards more strategic areas such as climate, the circular economy, diversity, governance and sustainable finance. Overall, the study highlights the co-evolution of digitalisation and sustainability narratives in Turkish corporate reporting; however, it emphasises that the increasing level of disclosure should be interpreted as an indicator of shifting communication priorities rather than as direct evidence of concrete performance.

1. Introduction

Digitalization and sustainability are two of the most significant factors affecting businesses in today's economy. For businesses, digitalization is not merely about process automation; it is a transformative component that yields strategic outcomes such as increased efficiency, enhanced innovation capacity, and resilience to shocks. At the firm level, classical studies have shown that information technology investments make a meaningful contribution to productivity and output growth in both the short and long term; they have also demonstrated that these effects become particularly pronounced when combined with organizational complements (Brynjolfsson and Hitt 2003; Bloom et al. 2012).

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Dynamic capabilities and the management practices that nurture them are critical for the success of digital transformation, as these capabilities serve as the mechanism through which digital technologies translate into firm performance (Ellström et al. 2022; Warner and Wäger 2019). Current evidence demonstrates that digitalization enhances firms' recovery speed and resilience during crises; during the COVID-19 pandemic, firms with high digital maturity recorded faster improvements in productivity and sales (Jaumotte et al. 2023; Nose 2023). Additionally, data-analytics-based applications have been associated with positive effects on labor productivity, wages, and sales growth in adopting firms (Agostino et al. 2022). Digitalization provides firms with both a competitive advantage and long-term value creation when technology investments are designed in harmony with organizational and managerial complements (Brynjolfsson and Hitt 2003; Bloom et al. 2012; Ellström et al. 2022).

For businesses, sustainability is not merely about managing environmental and social risks; it is directly linked to outcomes such as long-term value creation, lower cost of capital, and increased innovation capacity. A comprehensive meta-analysis has shown that the relationship between ESG practices and corporate financial performance is mostly positive or at least not negative, thereby strengthening the business case (Friede et al. 2015). Findings that companies focusing on material sustainability issues consistently outperform their peers in both accounting metrics and market performance demonstrate that allocating resources to the right themes creates value (Khan et al. 2016). It has also been shown that companies with a strong sustainability culture exhibit stronger stakeholder management, a long-term orientation, and better financial results (Eccles et al. 2014). At the conceptual level, the shared value creation approach argues that integrating social needs into business strategy can enhance competitiveness by generating efficiency gains, access to new markets, and reputational benefits (Porter and Kramer 2011). Also, the OECD's Global Corporate Sustainability Report 2025 highlights that sustainability-focused corporate governance and disclosures support companies' resilience and long-term growth capacity and emphasizes that mandatory sustainability disclosures are rapidly gaining traction on a global scale (OECD 2025).

The relationship between digitalization and sustainability emerges as a complementary dynamic, driven both by gains in efficiency and resource effectiveness within internal business processes and through external communication and stakeholder trust: meta-analyses indicate that investments in digital transformation generally have a positive impact on sustainable business performance, encompassing economic, environmental, and social dimensions (Bindeeba et al. 2025). At the firm level, digitalization enhances the likelihood of sustainable innovation, thereby strengthening the innovation channel leading to environmental performance (Ardito et al. 2019). At the regional level, digital infrastructure and digital maturity improve firms' ESG performance, particularly through the environmental information disclosure channel (Zhang et al. 2025).

Although the literature has examined corporate digitalization and sustainability reporting, these research streams remain largely fragmented. Existing research on BIST-listed companies has primarily focused on sustainability disclosures, integrated reporting, GRI compliance or sector-specific samples (Gücenme Gençoğlu and Aytaç 2016; Karadeniz and Uzpak 2020; İşseveroğlu 2021). Studies in the field of digitalisation, on the other hand, have mostly been addressed within the framework of digital corporate social responsibility, banking applications or the financial impacts of digital transformation in specific sectors (İyicil 2021; Güler 2022; Bıyıklı 2025). A recent study, whilst examining Industry 4.0 technologies within the context of sustainability, is limited to the 2023 sustainability reports of BIST 50 companies (Yılmaz Gezgin 2026). Consequently, there is limited evidence regarding how the themes of digitalisation and sustainability have evolved together over time within the broader BIST 100 reporting universe, whether structural breaks exist in these development processes, and how these changes can be compared with established themes of governance, financial performance and innovation. This study aims to address this gap by analysing annual reports from the 2015-2024 period. To this end, a combination of lexicon-based measurement, trend and structural break tests, TF-IDF, LDA and sustainability sub-theme analysis is employed.

It is important to address this research gap, as digitalisation and sustainability are no longer regarded as separate organisational priorities, but rather as two interconnected core dimensions of the 'twin transition' process. The interaction between these two dimensions can generate significant synergies in areas such as resource efficiency, emissions monitoring and sustainable innovation. However, the fact that digital technologies also generate significant environmental footprints demonstrates that digital and green transformation processes do not progress in a naturally aligned manner (European Commission

2022; Muench et al. 2022). Therefore, a long-term analysis is required to distinguish temporary reporting responses from more permanent structural transformations linked to regulatory changes, technological advances and external shocks.

Findings derived from BIST 100 companies extend the current understanding of the twin transition to the context of emerging markets and provide a pre-standardisation reference point against which future reporting developments can be assessed. This is particularly important given that standardised sustainability disclosures can influence investor decisions and capital allocation (Nipper et al. 2022). Finally, monitoring shifts in corporate discourse helps to assess whether the growing interest in digitalisation and sustainability signals a concrete strategic transformation, or whether it primarily reflects a quest for symbolic compliance and legitimacy (Meyer and Rowan 1977; DiMaggio and Powell 1983). However, reporting discourse should be interpreted not as direct evidence of actual improvements in digitalisation or sustainability performance, but as an indicator of corporate interest and prioritisation trends.

The remainder of this article is structured as follows: the next section discusses the theoretical framework guiding the analysis; this is followed by an explanation of the dataset and methodology used in the analysis of the BIST100 annual reports. The subsequent section presents findings relating to lexicon-based topic trends, structural break tests, LDA-based validation and sustainability sub-themes. Finally, in the discussion and conclusion sections, these findings are evaluated in the context of changing corporate reporting priorities, theoretical implications, methodological limitations and directions for future research.

2. Theoretical framework

It should be emphasised that annual reports are not merely documents presenting corporate information in an impartial manner; they are also strategic communication tools through which companies highlight their priorities, respond to external expectations and build their corporate identity. In this context, this study examines stakeholder theory, legitimacy theory, corporate theory and the concept of "decoupling" in conjunction to explain the changes in the discourse of BIST100 companies. These theoretical approaches offer complementary levels of explanation. Whilst stakeholder theory contributes to understanding the target audiences and information demands that shape companies' information disclosure, legitimacy theory explains how reporting is strategically utilised to respond to external expectations and maintain social acceptance. Institutional theory enables us to make sense of the similarities in reporting practices and their evolution over time; whilst the concept of "decoupling" highlights that corporate discourse should not be equated directly with concrete organisational practices.

Stakeholder theory argues that companies should be accountable not only to shareholders, but also to a wider range of stakeholder groups who are affected by, or influence, their corporate activities (Freeman 1984). In today's business environment, investors, regulatory bodies, employees, customers and society at large are demanding more comprehensive information regarding companies' levels of technological readiness and their environmental and social impacts. This growing demand for information is prompting companies to broaden the scope of their disclosures. The development of sustainability and integrated reporting practices in Turkey also demonstrates that stakeholders' expectations regarding transparency, accountability and long-term value creation have strengthened (Gücenme Gençoğlu and Aytaç 2016; Aksoy Hazır 2024). In this context, the increasing prevalence of references to digitalisation and sustainability themes in annual reports points not only to a transformation in the information environment but also to an expansion of the concept of corporate value. This study evaluates the theoretical possibilities offered by stakeholder theory to explain the accelerating development of non-financial themes when compared to traditional management and financial themes.

Legitimacy theory posits that companies operate within the framework of an implicit social contract and use corporate disclosure as a strategic tool to maintain or re-establish harmony between the actions of organisations and societal expectations (O'Donovan 2002). In this regard, annual reports play a significant role in enabling companies to present themselves as modern, responsible and environmentally conscious actors. Whilst discourses on digitalisation highlight companies' capacity for adaptation, their level of innovation and their technological competence, discourses on sustainability can reflect the concept of responsible corporate citizenship and alignment with environmental, social and governance expectations (İyicil 2021; İşseveroğlu 2021).The legitimising pressures experienced by firms may be augmented by regulatory developments, external shocks and shifting public expectations. Any acceleration or structural breaks in these themes may be indicative of firms' endeavours to preserve or re-establish social acceptance. The adoption of similar structures, practices and discourses by firms operating in a shared environment is explained by institutional theory. DiMaggio and Powell (1983) propose a taxonomy of isomorphisms, distinguishing between coercive, mimetic and normative forms. In the context of corporate reporting, regulatory frameworks and global reporting standards have the potential to engender coercive pressures. The emulation of leading firms can give rise to mimetic pressures, while professional norms and reporting expertise can generate normative pressures. The increasing importance of integrated and sustainability reporting in Turkey signifies the institutionalisation of non-financial disclosure, rather than its status as an isolated corporate choice (Gücenme Gençoğlu and Aytaç 2016). Concurrent escalations, congruence across enterprises, or structural disruptions in the discourse on digitalisation and sustainability may be indicative of the institutionalisation of the twin-transition agenda.

The concept of decoupling presents a significant interpretative boundary for research based on disclosure and reporting. Meyer and Rowan (1977) argue that formal structures and organisational reporting practices may sometimes be adopted for ceremonial or symbolic purposes; however, these structures may remain partially detached from the organisation's actual operational practices. Consequently, the widespread use of terminology relating to digitalisation or sustainability in annual reports may indicate a concrete strategic transformation, symbolic alignment, or the coexistence of both. Differences in the scope and nature of sustainability reporting also demonstrate that the intensity of disclosure does not always equate to equivalent organisational performance (Karadeniz and Uzpak 2020). In this study, word frequencies, trends and topic structures are assessed not as direct measures of technological competence or sustainability performance, but as indicators of corporate interest and communication priorities.

Taken as a whole, these four theoretical approaches provide a comprehensive framework for interpreting the evolution of corporate reporting discourse. Whilst stakeholder theory explains the expectations and pressures driving companies to disclose more comprehensive information, legitimacy theory reveals the rationale behind the use of digitalisation and sustainability themes as strategic communication tools. Corporate theory contributes to understanding why reporting language may converge over time and transform collectively; whilst the concept of differentiation emphasises that the information disclosed should not be regarded as a definitive indicator of concrete organisational practices. This holistic approach enables a meaningful link to be established between changes in the language used in annual reports and transformations in the external information environment. At the same time, it maintains that an analytical distinction must be made between corporate discourse and actual performance.

The study thus seeks to address the following primary research question: The evolution of digitalization and sustainability discourses in the annual reports of BIST100 companies during 2015-2024, and the attendant transformation in corporate reporting priorities, are the subject of this study. The empirical analysis examines the research question through five complementary analytical dimensions: digitalisation, sustainability, management, financial themes, and the temporal evolution of the R&D and innovation discourse; the identification of statistically significant trends and structural breaks; the relative growth dynamics of emerging themes compared to traditional reporting themes; cross-validation of lexical-based findings via the Latent Dirichlet Allocation method; and an analysis of the sub-themes driving the sustainability discourse. The theoretical framework predicts that corporate interest in digitalisation and sustainability will increase over time, that certain convergence trends and structural changes may emerge under shared external pressures, and that reporting priorities may be reordered. However, this framework does not definitively determine whether these discursive shifts represent a substantive strategic transformation or merely a quest for symbolic alignment and legitimacy.

3. Data and methodology

This study employs text-mining and natural language processing techniques to examine changes in corporate discourse through annual reports published between 2015 and 2024. The analytical process consists of four stages: (i) data collection, (ii) data preprocessing, (iii) dictionary-based topic analysis supported by descriptive and statistical tests, and (iv) cross-validation of the findings through unsupervised topic modeling using Latent Dirichlet Allocation (LDA).

3.1. Dataset

The dataset consists of annual reports covering the 2015-2024 period. The reports were obtained in PDF format from corporate websites and the Public Disclosure Platform of Türkiye. The number of reports processed annually increased from 57 in 2015 to 78 in 2024, and the dataset contains more than 710 documents in total. The corpus comprises approximately 39 million words. Annual text volume increased from approximately 2.5 million words in 2015 to approximately 6 million words in 2024, indicating growth in both the number of reports included in the sample and the average report length. The sample covers publicly traded companies operating in banking, manufacturing, energy, retail, transportation, and service industries. Although this cross-sectoral heterogeneity prevents the findings from being restricted to a single industry, it should be considered when interpreting results that may be affected by sectoral composition, particularly the LDA topics.

3.2. Data preprocessing

The raw text extracted from the PDF files was processed in Google Colab using the Python programming language and the pypdf, nltk, pandas, scikit-learn, and gensim libraries. The following preprocessing steps were applied sequentially:

(i) Text extraction: The textual content of each PDF file was read page-by-page using the pypdf library and converted into plain text.

(ii) Lowercase conversion: All text was converted to lowercase using Turkish-specific character mappings, including "İ -> i" and "I -> ı".

(iii) Noise removal: Numerical values, punctuation marks, special characters, and redundant whitespace were removed using regular expressions.

(iv) Stopword removal: In addition to the Turkish stopword list available in the NLTK library, a context-specific stopword list was developed for frequently occurring terms with limited analytical distinctiveness in annual reports, such as "year", "company", "report", "table", "million", and "TL".

3.3. Analytical methods

3.3.1. Dictionary-based topic analysis

A dictionary-based approach was adopted to measure the thematic content of the annual reports. The method aggregates the frequencies of predefined keyword pools and enables transparent and reproducible comparisons across years. Based on a review of the relevant literature and corporate reports, five main themes were identified: Management, Financial Data, Digitalization, Sustainability, and R&D and Innovation. Representative keyword pools were developed for each theme, and annual frequencies were calculated.

The predefined topic structure was developed through a deductive and purpose-driven content analysis procedure. Consistent with the principle that coding categories should be derived from the research question, theoretical framework, and communication context, the five topics were selected to facilitate a longitudinal comparison between traditional corporate-reporting priorities and emerging transformation-oriented priorities (Krippendorff 2018). Management and Financial Data represent the conventional core of annual reports, whereas Digitalization and Sustainability represent the two principal dimensions of the twin-transition agenda examined in this study. R&D and Innovation was included as a complementary bridging category reflecting the relationship between firms' technological transformation and innovation-oriented activities. The initial keyword pools were compiled through a review of the relevant literature and commonly used terminology in corporate reports and were subsequently refined by examining a sample of annual reports. Because the validity of dictionary-based analyses depends on the contextual meaning of terms within the examined domain, synonyms, alternative expressions, and relevant multi-word phrases were included, while highly ambiguous and analytically non-distinctive terms were excluded where possible (Loughran and McDonald 2011). Finally, the predefined thematic structure was compared with the latent topics identified by the LDA model as a robustness check, consistent with recommendations that automated text-analysis results should be validated using complementary methods and substantive domain knowledge (Grimmer and Stewart 2013).

3.3.2. Trend and structural-break tests

The direction, rate, and structural turning points of the frequency series were examined using three methods. The compound annual growth rate (CAGR) summarizes the average annual growth of each theme during the 2015-2024 period and facilitates comparisons across themes. The non-parametric Mann-Kendall trend test was used to assess the statistical significance of increasing trends; rejection of the null hypothesis at $p < 0.05$ indicates the presence of a statistically significant trend. Structural breaks were identified by applying the PELT (Pruned Exact Linear Time) algorithm from the ruptures library with an RBF kernel. This method detects years in which the statistical behavior of a series changes substantially.

3.3.3. TF-IDF

Term Frequency-Inverse Document Frequency (TF-IDF) scores were calculated to complement the dictionary-based approach and identify terminology that distinguishes individual years. In addition, proportional frequency differences between words used in 2015 and 2024 were calculated to directly examine shifts in corporate discourse.

3.3.4. LDA topic modeling

Because the dictionary-based approach relies on researcher-defined themes, a Latent Dirichlet Allocation model was used as an unsupervised robustness check of the identified thematic structure. Each PDF document was divided into chunks of approximately 5,000 tokens, producing 7,136 text documents, and the model was trained using the gensim library. The optimal number of topics was assessed by comparing c_v coherence scores for models ranging from $k = 3$ to $k = 10$. To facilitate comparison with the dictionary-based analysis, the main model was trained with $k = 5$.

3.3.5. Sustainability subtheme analysis

To decompose the drivers of growth within the Sustainability theme, the dictionary-based approach was reapplied to eight subthemes derived from the ESG framework: (i) Climate and Carbon Management, (ii) Energy and Renewable Resources, (iii) Environment and Circular Economy, (iv) Human Resources and Employee Well-being, (v) Diversity and Inclusion, (vi) Community and Social Responsibility, (vii) Sustainability Governance and Reporting, and (viii) Sustainable Finance. Frequencies and CAGR values were calculated for each subtheme.

4. Results

4.1. Frequency distribution of topics by year

Overall, a look at Figure 1 reveals that the word count of activity reports has increased over the years. This indicates that the importance of activity reports has grown and that more resources are being allocated to their preparation. When analyzed by topic, the "Management" topic increased from 76,500 in 2015 to 143,900 in 2024. This represents an approximate 88% increase. Management topics (board of directors, risk management, internal processes, organizational structure) have increasingly occupied more space in the reports, which aligns with rising corporate governance standards and heightened expectations for transparency.

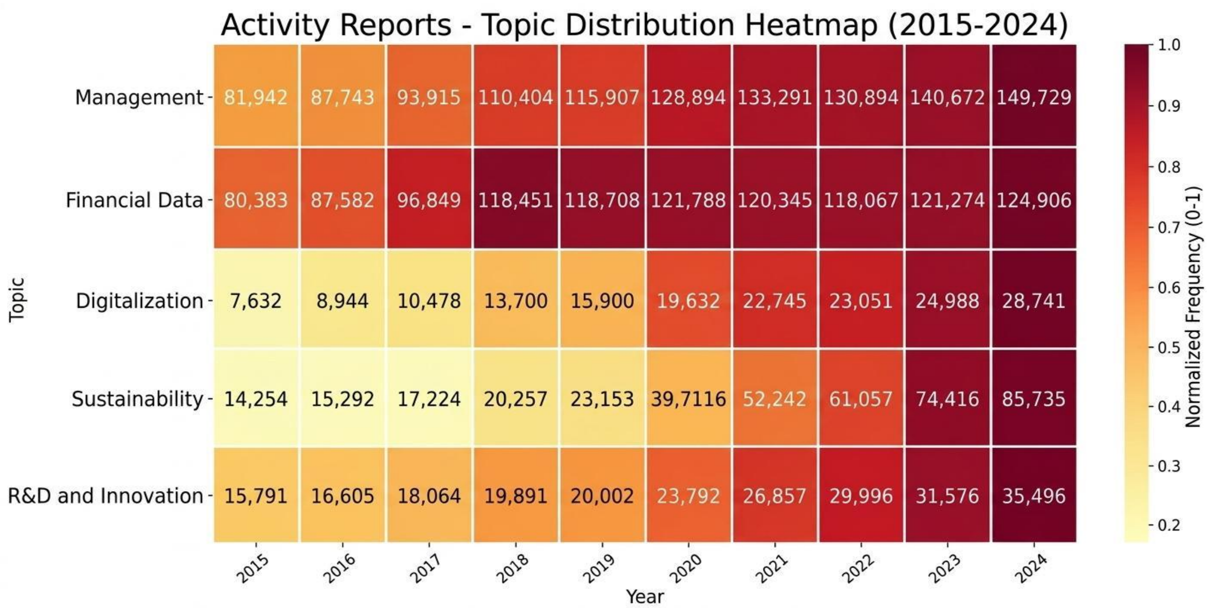

Figure 1. Heat map showing the distribution of topics by year

4.2. Growth rates

Table 1 present the compound annual growth rates of the themes for the 2015-2024 period. The Sustainability theme has the highest annual growth rate at 22.06%; this is followed by Digitalization at 15.87%. While the R&D and Innovation theme shows moderate growth of 9.42%, the Management theme has grown more slowly at 6.93%, and the Financial Data theme at 5.02%. The total growth rates of Sustainability and Digitalization, 501.5% and 276.6%, respectively, indicate that corporate discourse has undergone a structural shift over the past decade. The observed total increases for Management (82.7%) and Financial Data (55.4%) appear to be roughly in line with the overall expansion in the volume of annual reports.

Table 1. Initial and final values of the variables and CAGR results

Topic	2015	2024	Total Growth (%)	CAGR (%)
Sustainability	14.254	85.735	%501,5	%22,06
Digitalization	7.632	28.741	%276,6	%15,87
R&D and Innovation	15.791	35.496	%124,8	%9,42
Management	81.942	149.729	%82,7	%6,93
Financial Data	80.383	124.906	%55,4	%5,02

4.3. Mann-Kendall trend test results

According to the results of the Mann-Kendall trend test, the upward trend for all five themes is statistically significant at the $p < 0.05$ level (Table 2). The Tau values for the Digitalization, Sustainability, and R&D and Innovation themes reached the 1.000 level; these findings formally confirm the monotonic increase pattern observed in Table 1.

Table 2. Mann-Kendall trend test results

Topic	Trend Direction	p-value	Tau
Management	Increasing	0.00017	0.956
Financial Data	Increasing	0.00421	0.733
Digitalization	Increasing	0.00008	1.000
Sustainability	Increasing	0.00008	1,000
R&D and Innovation	Increasing	0.00008	1,000

4.4. Structural break points

When the PELT algorithm was applied, a structural break was identified in 2019 for the Digitalization and Sustainability themes; the other three themes exhibited a steady growth pattern throughout the period and did not show a significant breakpoint.

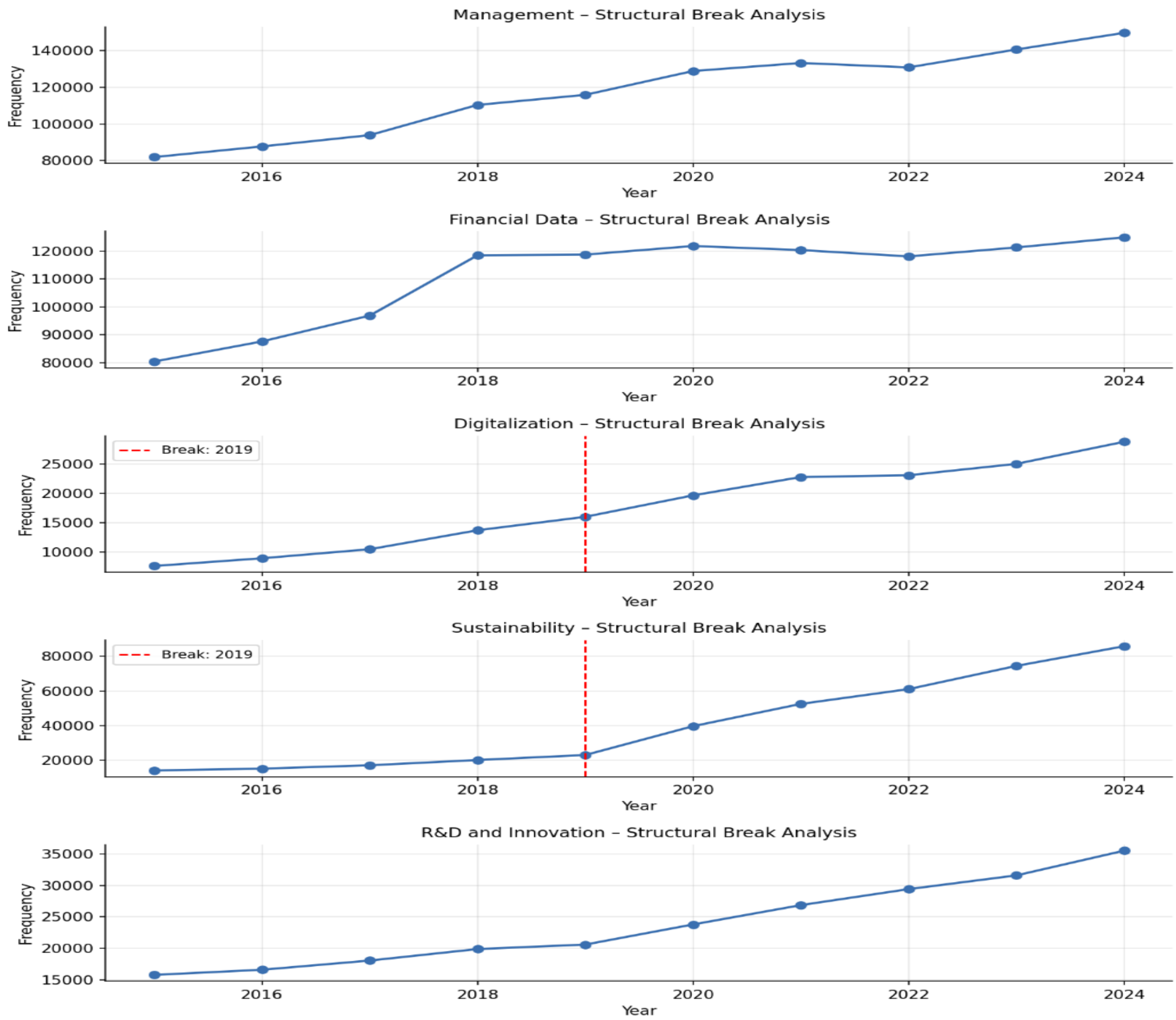

Figure 2. Structural break analysis of themes

The 2019 breakpoint in Sustainability aligns with developments in the regulatory framework of the period. The announcement of the European Green Deal in December 2019, the widespread adoption of TCFD recommendations, and updates to GRI standards led to a marked intensification of corporate expectations regarding sustainability reporting in that year. Regarding the establishment of the digitalization inflection point in 2019, it is assessed that the delay in the reflection of digital transformation projects in operational reporting, along with regulations published by domestic regulatory bodies (BDDK, SPK) regarding digital infrastructure during this period, played a role. The accelerating effect of the COVID-19 pandemic on the digitalization narrative is observed in the high trajectory of the series values in 2020 and beyond (Figure 2).

4.5. LDA

An LDA model was applied to test whether the findings obtained through the lexicon-based approach were supported by an unsupervised method. The c_v coherence scores calculated for the number of topics ranging from k = 3 to k = 10 are presented in Figure 3. The highest coherence score was obtained at k = 4 (c_v = 0.69); for k = 5, it was measured at c_v = 0.64. To ensure comparability with the five-theme structure of the dictionary-based approach, the main model was trained with k = 5. This choice results in a slight loss of coherence for the unsupervised model and should be considered among the methodological limitations of the study.

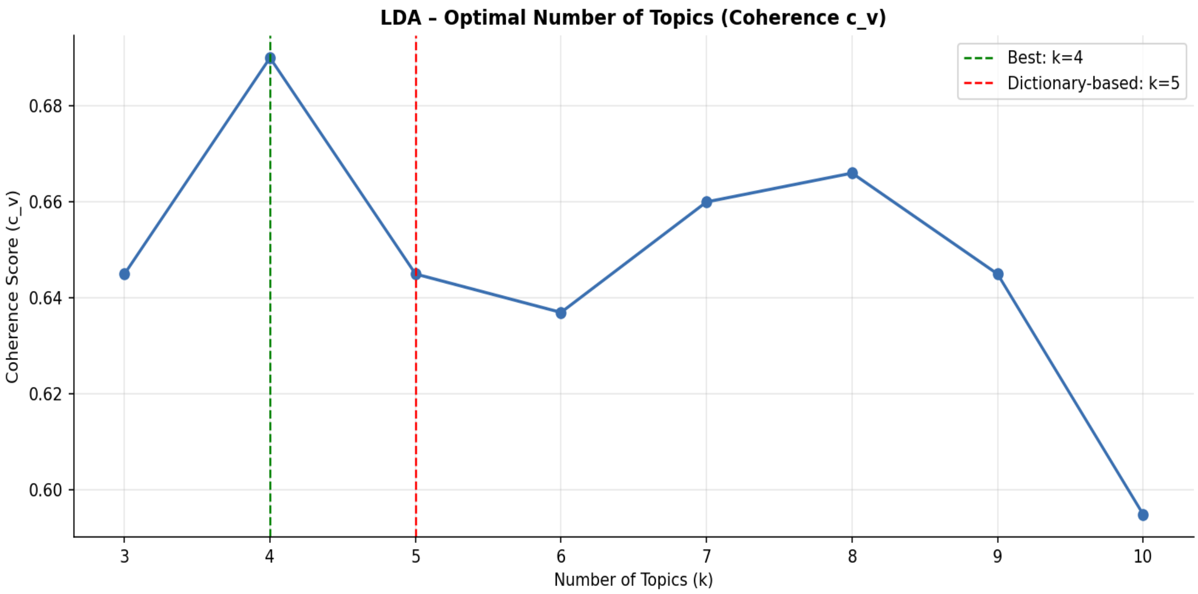

Figure 3. Optimal number of topics based on coherence scores for LDA

The five latent topics identified by the LDA model were labeled as follows, taking into account the weighted words they contain:

- Topic 1 - Banking and Credit Activities (bank, credit, consolidated, interest, receivables)
- Topic 2 - Corporate Governance and Audit (corporate, independent, audit, board, committee)
- Topic 3 - Digital and Sustainable Transformation (customer, integrated, digital, sustainable, climate)
- Topic 4 - Manufacturing, Energy, and Sectoral Operations (energy, manufacturing, product, sustainability)
- Topic 5 - Financial Reporting and Accounting (consolidated, tax, cash, financial statements, lira)

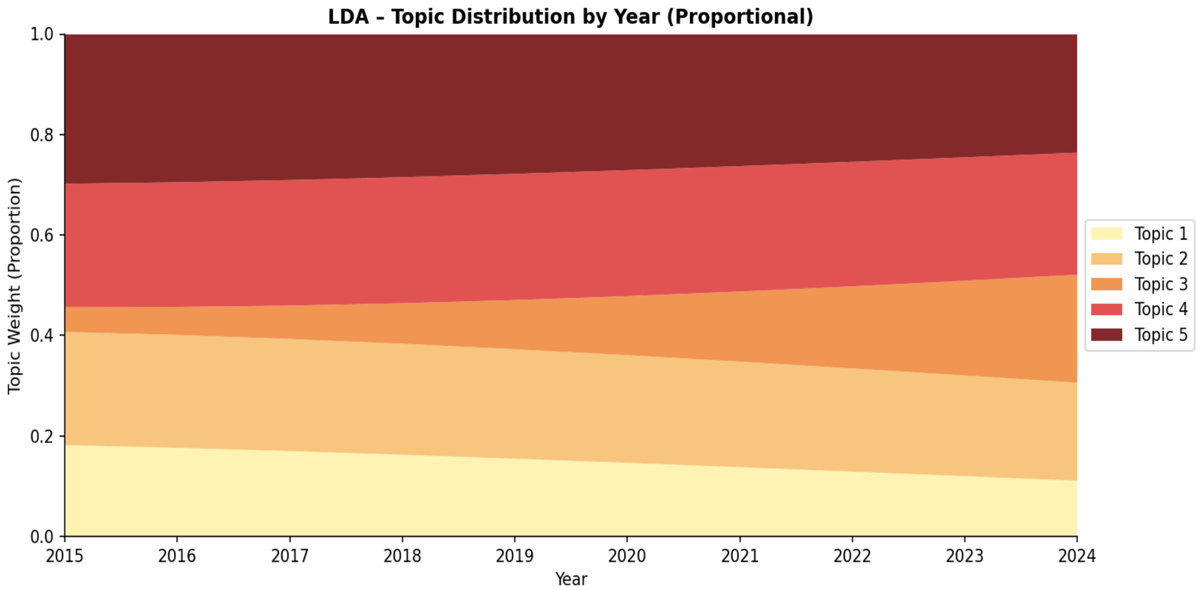

Figure 4. Proportional distribution of topics by year according to LDA

Figure 4 presents the average topic weights by year. The share of Topic 3 (Digital and Sustainable Transformation) rose from 5.0% in 2015 to 21.5% in 2024; this is the fastest-growing topic cluster. In contrast, the weights of Topic 1 (Banking and Credit) and Topic 5 (Financial Reporting) decreased over the period (from 18.2% to 11.1% and from 30.0% to 23.7%, respectively). When interpreting this decline, it should be noted that Topic 1 may also have been influenced by changes in the sectoral composition of the sample, as it captures terminology specific to the banking sector. The weights of Topic 2 (Corporate Governance) and Topic 4 (Energy and Manufacturing) remained relatively stable.

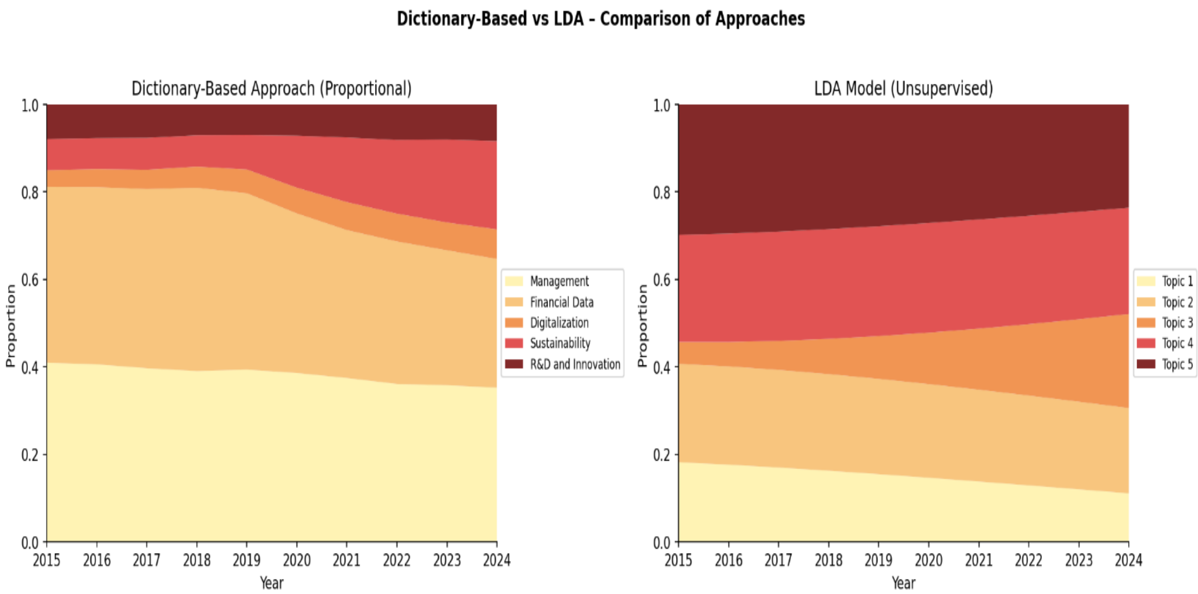

Figure 5. Comparison of the dictionary-based approach and the LDA model

Figure 5 presents the annual proportional distributions of the two methods side by side. Both approaches align on the same core finding. The proportional share of traditional financial discourse is decreasing, while topics related to sustainability and digital content are increasing. Although the dictionary-based approach is limited to the word pools defined by the researcher, the fact that it reveals similar trends to the LDA model, which learns from the data unsupervised, demonstrates that the dictionary-based inferences are supported by the data.

A topic-level comparison indicates substantial but not one-to-one correspondence between the predefined structure and the LDA results. Because the predefined topics were designed to measure theoretically relevant reporting priorities, whereas LDA grouped terms according to their empirical co-occurrence patterns, convergence between the two approaches provides evidence of thematic robustness, while differences reveal the sectoral and cross-cutting structure of the corpus.

Table 3. Comparison of predefined topics and LDA-derived topics

Predefined topic	Closest LDA-derived topic(s)	Correspondence	Interpretation
Management	Topic 2: Corporate Governance and Audit	Strong	Governance, board, committee, and audit terminology forms a distinct latent cluster.
Financial Data	Topic 5: Financial Reporting and Accounting; Topic 1: Banking and Credit Activities	Strong but divided	General financial reporting is separated from banking-specific credit and interest terminology.
Digitalization	Topic 3: Digital and Sustainable Transformation	Strong but combined	Digital concepts co-occur with sustainability concepts rather than forming an isolated cluster.
Sustainability	Topic 3: Digital and Sustainable Transformation; Topic 4: Manufacturing, Energy, and Sectoral Operations	Strong but distributed	Sustainability appears both as a transformation discourse and as part of operational and energy-related reporting.
R&D and Innovation	Topic 3: Digital and Sustainable Transformation; Topic 4: Manufacturing, Energy, and Sectoral Operations	Partial	Innovation-related terms are distributed across transformation and operational contexts and do not form an independent latent topic.

The strongest correspondence is observed between the predefined Management topic and LDA Topic 2, and between Financial Data and LDA Topic 5 (Table 3). However, financial terminology is divided between the general financial-reporting cluster and the sector-specific Banking and Credit cluster. Digitalization and Sustainability, which were measured separately in the predefined structure, converge within LDA Topic 3; this result independently supports the interpretation that the two themes increasingly form a joint twin-transition discourse. Sustainability terminology also appears in Topic 4 because environmental and energy-related concepts are embedded in sectoral operations. In contrast, R&D and Innovation does not emerge as an independent latent topic and is distributed mainly across the transformation and operational clusters. Overall, LDA validates the main substantive distinction between traditional reporting and emerging transformation themes, but also shows that some predefined concepts overlap or become sectorally differentiated in naturally occurring corporate discourse.

4.6. Analysis of sustainability sub-themes

The results of the analysis conducted to decompose the components of the growth in the sustainability theme are presented in Figures 6-9.

According to Figure 6, all sub-themes have intensified since the 2019-2020 turning point. The Climate and Carbon Management sub-theme rose from a frequency of 1,634 in 2019 to 4,482 in 2020; it continued to increase in subsequent years, reaching 14,870 in 2024. Human Resources and Employee Well-being was the sub-theme with the highest absolute frequency throughout the period.

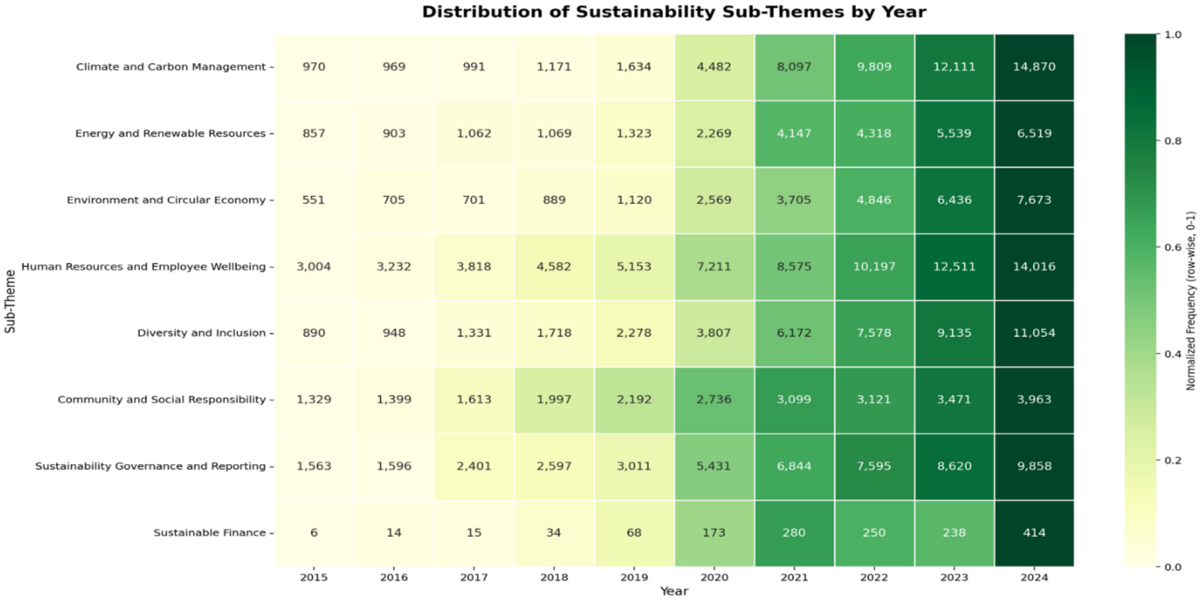

Figure 6. Distribution of sustainability sub-themes by year

Figure 7 shows the absolute volume contributions of the sub-themes. The total volume of the sustainability theme rose from approximately 9,200 in 2015 to 68,400 in 2024. The sub-themes of Climate and Carbon Management and Human Resources and Employee Well-being contribute the most to the total volume.

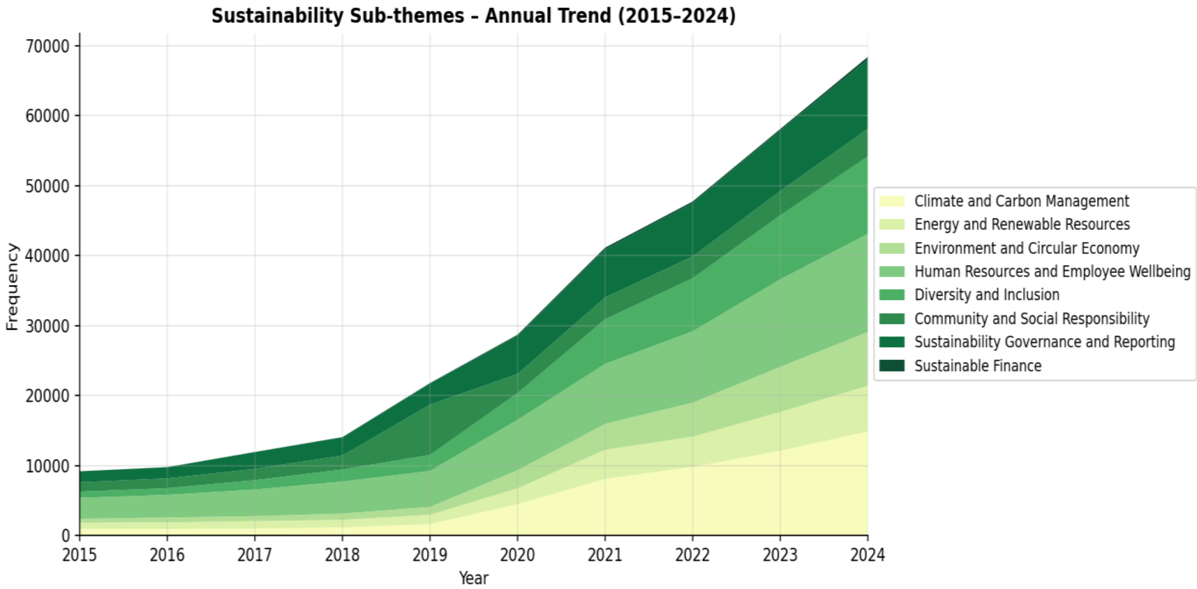

Figure 7. Annual cumulative distribution of sustainability sub-themes

The proportional distribution chart (Figure 8) illustrates how the relative weights of the sub-themes within their respective categories have changed over the years. While Human Resources and Employee Well-being held the largest share within sustainability in 2015, its relative share has decreased somewhat over time. In contrast, the shares of the Climate and Carbon Management and Diversity and Inclusion sub-themes have increased. The proportional share of the Society and Social Responsibility sub-theme has decreased; this indicates that the sustainability discourse is shifting from the traditional focus on "corporate social responsibility" toward environmental and governance dimensions.

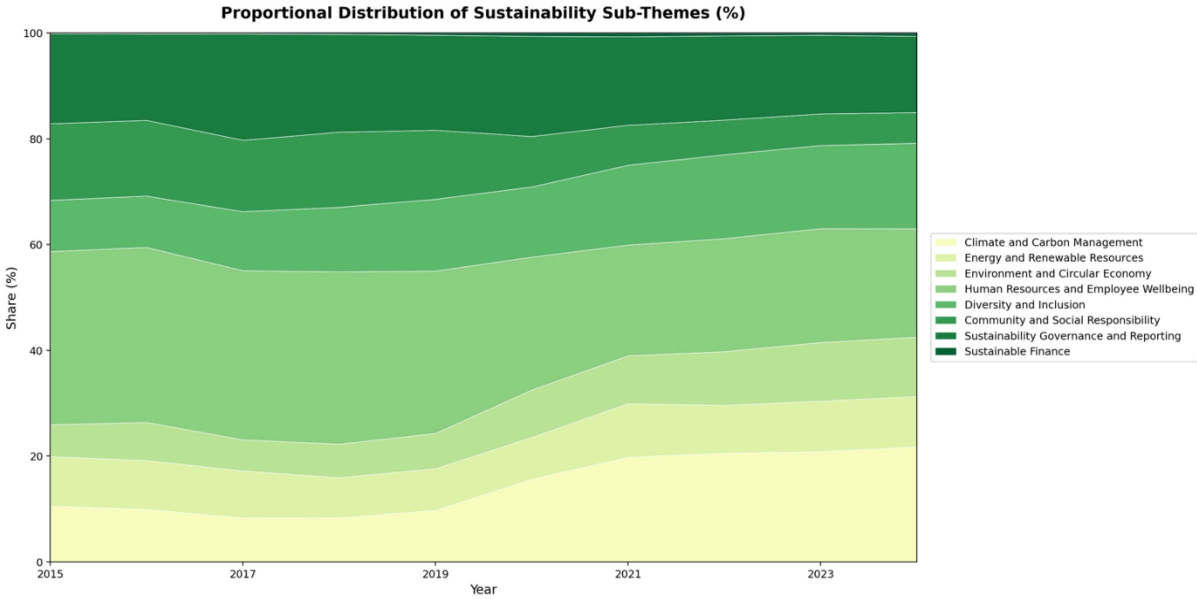

Figure 8. Proportional distribution of sustainability sub-themes

Figure 9 and Table 4 present the CAGR values for the sub-themes. The Sustainable Finance sub-theme has the highest annual growth rate at 60.07%; however, Figure 9 is based on a very low initial baseline (only 6 mentions in 2015), and the absolute volume it reached by the end of the period remained more limited compared to other sub-themes (414 in 2024). Climate and Carbon Management (35.43%), Environment and Circular Economy (34.00%), and Diversity and Inclusion (32.30%) follow with high growth rates. Developments in these areas align with the adoption of ESG reporting standards (TCFD, GRI, SASB). Society and Social Responsibility (12.91%) and Human Resources and Employee Well-being (18.67%) are among the slowest-growing sub-themes; these areas can be considered categories with a relatively mature baseline.

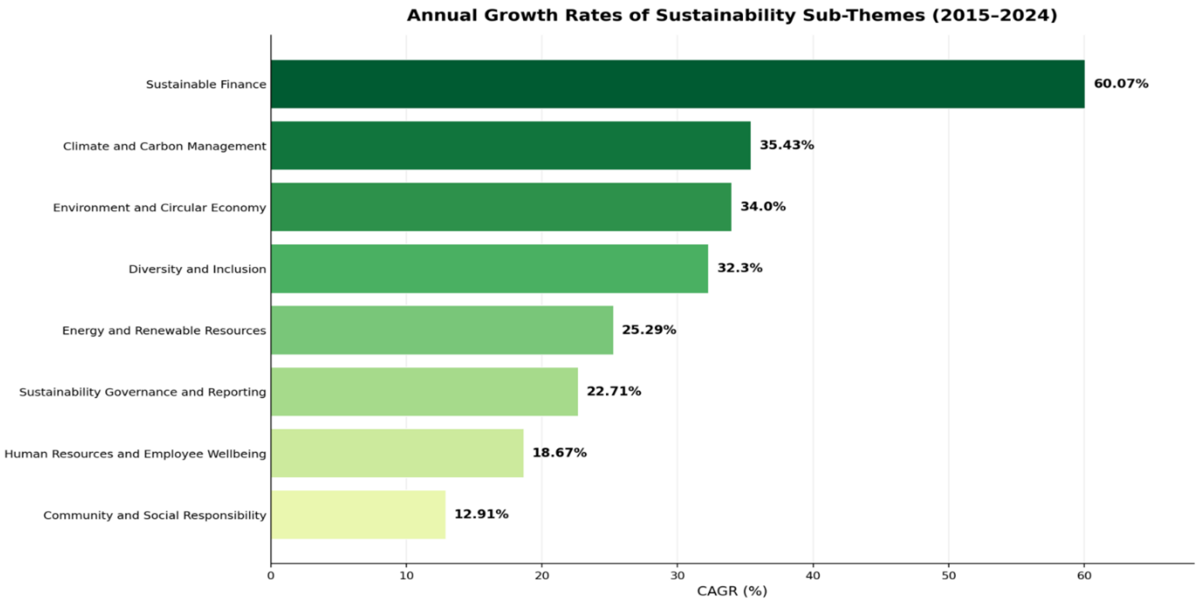

Figure 9. Compound annual growth rates of sustainability sub-themes

Table 4. Initial and final values of sustainability sub-themes and CAGR results

Sub-Theme	2015	2024	Total Growth (%)	CAGR (%)
Sustainable Finance*	6	414	%6.800.0	%60,07
Climate and Carbon Management	970	14.870	%1,433.0	%35,43
Environment and Circular Economy	551	7,673	%1,292.6	%34,00
Diversity and Inclusion	890	11,054	%1,142.0	%32,30
Energy and Renewable Resources	857	6,519	%660.7	%25,29
Sustainability Governance and Reporting	1,563	9,858	%530.7	%22,71
Human Resources and Employee Well-being	3,004	14,016	%366,6	%18,67
Community and Social Responsibility	1,329	3,963	%198.2	%12,91

Note: * The reported 60.07% CAGR for Sustainable Finance includes a low-base effect due to the 2015 baseline having only 6 observations; when interpreting this, it should be noted that the sub-theme's absolute volume in 2024 (414) remains limited compared to other sub-themes.

5. Discussion

The research findings answer the main research question by revealing that the reporting priorities of BIST100 companies changed significantly during the 2015-2024 period. Whilst the themes of management and financial data retained their leading positions and continued to show an increase in absolute terms, the growth rates in these areas lagged behind those of the sustainability and digitalisation themes. The sustainability theme recorded a 501.5 per cent increase, reaching a CAGR of 22.06 per cent, whilst the digitalisation theme recorded a 276.6 per cent increase, achieving a a CAGR of 15.87 per cent. In contrast, the increases in the management and financial data themes stood at 82.7 per cent and 55.4 per cent, respectively. This trend indicates that traditional reporting priorities have not lost their importance; however, they are increasingly being complemented by transformation-focused non-financial themes. Corporate reporting is evolving from a structure focused primarily on financial performance and governance towards one that more broadly encompasses the dimensions of long-term value creation, technological readiness, environmental responsibility and social impact.

The rapid growth in the themes of digitalisation and sustainability is consistent with the predictions of stakeholder theory. According to this theory, companies are expanding the scope of their disclosures in response to the increasing demand for information from various stakeholder groups, such as investors, regulatory bodies, employees, customers and society (Freeman 1984). The fact that these themes are becoming increasingly prominent in annual reports indicates that stakeholders now assess companies not only on the basis of their financial results, but also on their level of technological readiness and their capacity to manage environmental and social risks. This observation is consistent with the development of sustainability and integrated reporting practices in Turkey; indeed, throughout this process, non-financial information has assumed an increasingly central role in terms of transparency and accountability (Gücenme Gençoğlu and Aytaç 2016; Aksoy Hazır 2024). The findings contribute to the existing literature by demonstrating that this transformation is not limited to sustainability reporting alone. Digital transformation has also become a key component of annual reporting discourse and has emerged as one of the defining themes in the reshaping of corporate reporting priorities.

The structural shift identified in 2019 in relation to both digitalisation and sustainability demonstrates that developments in these areas are not merely a natural extension of the general expansion of annual reports. Viewed from the perspective of instutional theory, this simultaneous shift is consistent with increasing coercive pressures arising from regulations and reporting standards, normative pressures stemming from professional reporting practices, and mimetic pressures driving companies to follow leading organisations (DiMaggio and Powell 1983). This timing coincides with the announcement of the European Green Deal, the growing influence of the TCFD and GRI frameworks, and increased national interest in digital infrastructure. The strong upward trend observed from 2020 onwards suggests that the COVID-19 pandemic, rather than independently triggering this process, accelerated the trend towards corporate compliance that had become apparent as early as 2019.

The theory of legitimacy offers a complementary explanation of this change. The increasing references to digital competence, climate action, ESG practices and responsible governance enable companies to position themselves as actors aligned with changing social and regulatory expectations

(O'Donovan 2002; İyicil 2021; İşseveroğlu 2021). Consequently, the common inflection point observed in the themes of digitalisation and sustainability, and the momentum that followed, may reflect efforts to maintain and strengthen corporate legitimacy at a time when technological resilience and sustainability performance are gaining greater visibility. However, the analysis reveals a temporal overlap rather than causal effects. Consequently, it is not possible to attribute this turning point definitively to a single regulation, reporting standard or external shock.

A comparison between predefined themes and the topics identified using the LDA method provides particularly significant evidence regarding the relationship between digitalisation and sustainability. The lexicon-based approach measured digitalisation and sustainability as independent themes in order to compare the development trends of these two concepts separately over time. In contrast, the unsupervised LDA model grouped these concepts under the heading "Topic 3: Digital and Sustainable Transformation"; the relative weight of this topic rose from 5.0 per cent in 2015 to 21.5 per cent in 2024. This convergence indicates that the concepts of digitalisation and sustainability are no longer treated as entirely separate reporting areas, but are increasingly being addressed within a shared corporate narrative. This finding supports the twin transition approach, which emphasises that digital technologies and the green transition are developing as mutually reinforcing strategic priorities (European Commission 2022; Muench et al. 2022).

The alignments between the remaining predefined themes and the LDA topics further clarify the reporting structure. Whilst the "Management" theme overlaps strongly with the "Corporate Governance and Audit" topic, the "Financial Data" theme is distributed between the general "Financial Reporting and Accounting" topic and the sector-specific "Banking and Credit Activities" topic. Sustainability, meanwhile, emerges in both the "Digital and Sustainable Transformation" and "Manufacturing, Energy and Sectoral Operations" topics; this demonstrates that sustainability functions both as a strategic discourse area and as an operational issue. The theme of R&D and innovation, however, does not constitute a distinct underlying theme; instead, the relevant terminology is distributed across transformation and operational contexts. This finding suggests that innovation is increasingly being reported not as a separate organisational priority, but as a mechanism enabling digital and sustainable transformation. At the same time, the absence of a distinct R&D theme indicates that the low growth in this area should not be interpreted solely as evidence of limited innovation activity.

An analysis of sustainability sub-themes shows that the rise in sustainability discourse reflects an internal reorganisation of priorities. Whilst the sub-theme of human resources and employee wellbeing has maintained a high level in terms of absolute frequency, the fastest growth has occurred in the areas of sustainable finance, climate and carbon management, the environment and the circular economy, as well as diversity and inclusion. The exceptionally high CAGR in the sustainable finance sub-theme should be interpreted with caution, given the very low initial frequency. Nevertheless, the general trend indicates that the sustainability narrative is shifting from an approach predominantly focused on philanthropy and corporate social responsibility towards a more strategic and measurable framework encompassing climate risk, resource efficiency, inclusivity, governance and standardised ESG reporting. This development is consistent with the increasing institutionalisation and standardisation of sustainability disclosures (Nipper et al. 2022).

The results support the holistic theoretical framework developed in this study. Stakeholder theory explains the increasingly broad scope of information demands reflected in annual reports, whilst legitimacy theory reveals why companies strategically highlight their alignment with expectations regarding digitalisation and sustainability. Institutional theory, meanwhile, contributes to explaining the simultaneous growth, convergence and structural changes observed across companies. The fact that digitalisation and sustainability converge under a common theme in the LDA analysis demonstrates that institutionalised reporting practices frame these areas not as independent initiatives, but increasingly as parts of an integrated strategic agenda.

However, the findings should be assessed within the interpretative boundaries indicated by the concept of decoupling. An increase in the level of disclosure may represent a concrete strategic transformation, a symbolic alignment, or a combination of both; however, word frequencies cannot directly demonstrate whether this corresponds to improvements in companies' technological capabilities or sustainability performance (Meyer and Rowan 1977; Karadeniz and Uzpak 2020). Consequently, the results reflect not direct changes in operational outcomes, but rather the transformation occurring in companies' areas of focus and communication priorities. This distinction is important because institutional and legitimacy pressures that encourage meaningful transparency may also support ceremonial, selective or predominantly positive disclosure practices.

This study contributes to the literature by jointly examining the themes of digitalisation and sustainability across a broad, cross-sectoral sample of BIST100 companies over a ten-year period. Previous studies in the Turkish context have generally addressed sustainability disclosures, digital corporate social responsibility, or sector-specific digitalisation issues separately. This study, however, utilises a combination of pre-defined topic measures, trend and structural break tests, TF-IDF, LDA-based cross-validation and sustainability sub-theme analysis to reveal both the scale and internal structure of changes in corporate reporting priorities. The alignment between the predefined approach and the LDA approach reinforces the robustness of the core finding, whilst the differences between the two approaches reveal sector-specific clusterings and conceptual overlaps that are difficult to capture using a single method.

Certain limitations still remain. Dictionary-based findings depend on the word pools defined by the researcher and, despite the use of contextual narrowing and LDA, may be affected by ambiguous or overlapping terms (Loughran and McDonald 2011; Grimmer and Stewart 2013). Although the highest consistency score was obtained at k = 4, an LDA model with k = 5 was preferred in order to enable comparison with the five predefined topics. Furthermore, changes in sectoral composition and differences in the number of available reports may affect topic frequencies and LDA weights. Future research is recommended to include company-level and sector-specific panel analyses, to compare the disclosed information with observable performance indicators and investment data, and to distinguish concrete commitments from general or symbolic references using contextual classification or embedding-based methods.

6. Conclusion

This study examined how digitalization and sustainability discourses evolved in the annual reports of BIST100 companies between 2015 and 2024 and what this evolution indicates about changing corporate-reporting priorities. The findings show that traditional financial and governance-related themes remained central, but were increasingly complemented by transformation-oriented non-financial themes. Sustainability increased by 501.5% and Digitalization by 276.6%, substantially exceeding the growth of Management and Financial Data. The structural break identified in 2019 for both themes further indicates that this change represents a reordering of reporting priorities rather than merely the general expansion of annual-report content.

The LDA results reinforce this conclusion. While the predefined analysis measured Digitalization and Sustainability separately, the unsupervised model combined them within the rapidly growing Digital and Sustainable Transformation topic. This convergence provides independent evidence that the two themes increasingly constitute a shared twin-transition discourse. The sustainability subtheme analysis further shows that the expansion of sustainability reporting is being driven increasingly by climate and carbon management, the circular economy, diversity and inclusion, and sustainable finance, rather than solely by traditional social-responsibility activities.

These findings contribute to the literature by demonstrating the joint and longitudinal evolution of digitalization and sustainability across a broad, cross-sectoral BIST100 reporting landscape. They also show the value of combining predefined topic measurement with LDA: the former enables theoretically focused comparison over time, while the latter reveals naturally occurring overlaps and sector-specific topic structures. However, the results concern changes in corporate attention and communication priorities. Increased disclosure cannot, by itself, establish corresponding improvements in technological capability, sustainability performance, profitability, or market value.

For companies, the findings underline the growing importance of communicating digital and sustainability strategies in an integrated, measurable, and decision-useful manner. More transparent links between stated priorities, R&D investments, implementation activities, and observable outcomes may strengthen the credibility of corporate reports. Future research should compare reporting discourse with firm-level investments and performance indicators, examine sector-specific differences, and apply contextual text-classification methods to distinguish substantive commitments from general or symbolic disclosure.

Declaration of competing interest

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

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Appendix 1: Word Pools

Main 5 Themes

Management: management, board of directors, CEO, executive board, audit, committee, appointment, assignment, organization, strategy, policy, procedure, decision, meeting, vote, share, share, partnership, independent member, salary, award, performance, goal, vision, mission, value, principle, transparency, accountability, internal control, risk management, compliance, legislation, regulation, bylaw, articles of association, general meeting, dividend, capital, shareholder

Financial Data: revenue, expenses, profit, loss, balance sheet, assets, liabilities, equity, debt, receivables, cash, investment, budget, cost, price, ratio, interest, exchange rate, inflation, tax, depreciation, turnover, sales, exports, imports, market, growth, increase, decrease, financing, credit, fund, bond, note, liquidity, profitability, efficiency, consolidated, gross, net

Digitalization: digital, technology, software, hardware, system, platform, application, mobile, internet, data, cloud, artificial intelligence, automation, cyber, security, infrastructure, integration, transformation, innovation, ERP, CRM, API, digitalization, e-commerce, robot, algorithm, analytics, machine learning, Internet of Things, blockchain, 5G, database

Sustainability: sustainability, environment, climate, carbon, emissions, energy, renewable, waste, recycling, water, biodiversity, ecosystem, green, ESG, social responsibility, community, employees, human rights, diversity, inclusion, workplace safety, health, education, donations, volunteering, supply chain, ethics, governance, net zero, Paris Agreement, TCFD, GRI, reporting

R&D and Innovation: research, development, innovation, patent, project, laboratory, university, collaboration, technology, product, prototype, testing, pilot, innovation, know-how, licensing, registration, brand, design, R&D, TUBITAK, incentive, grant, venture, startup, ecosystem, R&D center, industry, production, efficiency

Sustainability Sub-Themes

Climate and Carbon Management: climate, climate change, carbon, carbon neutral, carbon footprint, carbon emissions, greenhouse gas, greenhouse gases, global warming, Paris Agreement, net zero, net-zero, net-zero, TCFD, carbon management, climate risk, carbon neutrality, carbon emissions, climate crisis

Energy and Renewable Resources: renewable, renewable energy, solar energy, wind energy, hydroelectric, biomass, geothermal, clean energy, energy efficiency, energy conservation, green energy, photovoltaic, solar, wind power plant, GES, RES, energy transition

Environment and Circular Economy: waste, waste management, recycling, circular economy, circular, water management, water consumption, wastewater, biodiversity, ecosystem, natural resources, air quality, environmental impact, environmental management, environmental protection, water footprint, recovery

Human Resources and Employee Well-being: employee, employees, employee engagement, occupational safety, occupational health, OSH, employee training, employee development, career, talent management, employee satisfaction, workplace safety, working conditions, human resources, workplace accident, health and safety

Diversity and Inclusion: diversity, inclusion, equal opportunity, gender equality, women, female employees, women's employment, female executives, people with disabilities, employment of people with disabilities, gender, equality, discrimination, inclusive, disadvantaged groups

Community and Social Responsibility: social responsibility, corporate social responsibility (CSR), donations, volunteering, social investment, social impact, contribution to society, social projects, sponsorship, philanthropy, NGOs

Sustainability Governance and Reporting: ESG, GRI, sustainability report, sustainability reporting, sustainability committee, sustainability policy, sustainability strategy, integrated report, integrated reporting, ethics, transparency, business ethics, SASB, materiality, stakeholder, stakeholders, bribery, corruption

Sustainable Finance: green bond, green bonds, green loan, green financing, sustainable loan, sustainability-linked loan, ESG investment, green investment, sustainable finance, green bond, climate finance, green investments

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Alternative credit scoring, loan repayment performance, and financial inclusion: Evidence from India's digital finance ecosystem

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Primary data

ABSTRACT

This study examines the usefulness of alternative data sources, including mobile payment activity, e-commerce spending, psychometric traits, and digital footprints, in assessing creditworthiness when traditional credit bureau scores are unavailable or incomplete. The study addresses the issue of financial exclusion in developing economies by evaluating whether these non-traditional indicators can effectively predict loan repayment behavior. Primary data were collected from 400 respondents in India using a structured questionnaire covering demographic characteristics, financial literacy, digital transaction behavior, psychometric attributes, and loan performance. Logistic regression analysis was employed to estimate the relationship between alternative credit indicators and the probability of default. Descriptive statistics, correlation analysis, and odds ratios were used to interpret the results, and traditional credit scores were incorporated where available for comparison. The results indicate that timely bill payments, higher frequency of UPI transactions, greater conscientiousness, and stronger digital footprint scores are significantly associated with a lower probability of default. In contrast, a larger number of existing loans and higher interest rates increase repayment risk. Although traditional credit bureau scores improve the predictive accuracy of the model, nearly half of the respondents lacked such scores, highlighting a substantial financial inclusion gap. The findings suggest that alternative data can serve as reliable indicators of creditworthiness and offer financial institutions an effective approach to extending credit access to underserved populations excluded from conventional credit evaluation systems.

1. Introduction

Access to low cost and easily available credit has been a key driver of inclusive economic growth; however, financial exclusion is one of the most prevalent problems in many emerging economies. Notwithstanding the rapid progress of digital finance in India, there are about 190 million unbanked adults in the country (World Bank 2022). Many people who hold a bank account are considered to be thin-file borrowers, having few or no credit records and essentially going undetected by traditional

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lenders (Allen et al. 2021; Inder et al. (2022). This exclusion perpetuates the use of informal credit markets at high interest rates and limits the ability of households to smooth consumption, of entrepreneurs to invest, and of overall economic participation (Serrano-Cinca and Gutiérrez-Nieto 2016).

Financial inclusion is key to reducing poverty and encouraging economic participation and inclusive growth. It is therefore a key policy goal for governments, financial institutions and regulators everywhere and has emerged as an important topic. Financial services are an essential ingredient for providing small businesses and people with access to financial options that are both affordable and appropriate. These services assist them to control risks, make investments in productive pursuits, and enhance their general economic wellbeing (Frost et al. 2019; Almlund et al. 2011). Despite the progress that has been achieved in enhancing access to finance, countless individuals continue to face challenges in obtaining formal financial services because they lack credit histories or proper documentation of their financial activities. The conventional credit scoring systems primarily rely on credit bureau data, banking history, and formal financial documents. This approach has posed significant challenges for first-time borrowers, informal sector workers, rural communities, and economically disadvantaged groups (Jagtiani and Lemieux 2018; Schuetz and Venkatesh 2020). Evaluating borrowers with less than perfect credit or no credit history has posed an intriguing challenge, resulting in a rise in alternative credit scoring methods. The digital revolution, along with the rise of connectivity and fintech innovation, has led to the emergence of new data types that can provide valuable insights into borrower behaviour and their ability to repay loans. Alternative indicators like digital payment transactions, mobile financial activities, online behavioural patterns, and psychometric characteristics are emerging as valuable tools that can enhance traditional credit assessment methods (Thomas et al. 2017). Alternative data sources may bridge the information gap between lenders and borrowers, potentially enhancing credit access for underserved groups (Berg et al. 2020). India is an important place to explore alternative credit scoring, especially when considering financial inclusion. The nation has experienced a remarkable transformation in digital finance over the past ten years, thanks to initiatives like the Pradhan Mantri Jan Dhan Yojana, Aadhaar-based digital identification, the Unified Payments Interface, India Stack, and the Account Aggregator framework. These developments have significantly boosted participation in digital finance and generated a vast amount of information from digital transactions that could be utilised for credit scoring (RBI 2024). The extensive adoption of UPI has opened up new opportunities to gain a better understanding of personal financial behaviours, insights that would typically be restricted to traditional banking data. Meanwhile, the Reserve Bank of India (RBI) has established regulations for digital lending, emphasising the importance of responsible innovation, transparency, and consumer protection (RBI 2024).

While alternative data has proven to have a predictive role in credit risk assessment, there are still many gaps that need to be filled. Much of the current literature is based on the developed world and specific datasets, which makes it difficult to generalise results to emerging economies. Secondly, previous studies have investigated digital behaviour, psychometric traits and financial literacy separately, rather than together, to assess the combined effect on the likelihood of repayment. Thirdly, there is a limited amount of empirical information available on the role of alternative credit scoring in the context of financial inclusion in India. Hence, a framework is needed to assess various aspects of borrower behaviour in the context of the distinct nature of the Indian digital financial landscape. This paper investigates the contribution of digital behavioural traits, psychometric characteristics and financial literacy measures in understanding loan repayment behavior of borrowers in India. In particular, it proposes a Digital Footprint Index and explores its predictive power in terms of repayment risk, based on digital transaction behaviours, psychological traits and financial literacy (BIS 2020). The study explores how alternative credit assessment mechanisms can help improve access to financial services for the population that may be excluded from traditional credit assessment mechanisms.

This study contributes to the literature in a number of ways. First, it brings together digital behavioural and psychometric characteristics and financial literacy assessments in a single analytical framework. Second, it offers empirical facts from India's dynamic digital finance sector, which goes beyond the context of wealthy countries. Third, it provides a glimpse into the potential of using non-traditional indicators as a tool in more inclusive lending decisions and as a topic for discussion on alternative credit scoring and financial inclusion. Last but not least, the results provide concrete recommendations for policy makers, financial institutions and fintech firms to ensure innovation, risk management and financial inclusion in the digital economy.

2. Literature review

2.1. International existing evidence on alternative credit scoring

Over the recent years, digital finance has already created new data streams that have predictive credit scoring. An analysis of online lending platforms in Germany (Berg et al. 2020) revealed that single variables of simple digital footprint, including email domain, device type, and time of application, were predictors of default risk nearly as well as bureau scores. On the same note, Jagtiani and Lemieux (2018) & Arner et al. (2016) showed that fintech lenders in the United States used the data related to bank account transactions and machine learning algorithms to grant credit to underserved groups without lowering repayment rates. The mobile top-up records, airtime purchase, and bill payment histories have been used in credit scoring models using mobile money services, which have expanded in Africa, including M-Pesa. In Kenya, it is reported to have strong correlation between these variables and repayment outcomes (FSD Kenya 2019). The same strategy has been implemented in Latin America, where fintechs evaluate e-commerce transactions patterns and online bill payments frequency to anticipate default. Psychometric testing in credit assessment has its roots in the microfinance. Karlan and Zinman (2010) as well as Klinger et al. (2013) demonstrated that psychometric questionnaires to measure conscientiousness, integrity, and locus of control could be an effective predictor of repayment behavior in Peru, Colombia, and South Africa. The instruments will come in very handy in cases where they have limited financial information available, and the lenders can assess the entrepreneurial qualities and repayment habits. According to Gupta et al. (2023), fintech companies in the emerging markets are becoming more and more integrated into digital loan applications, which use psychometric testing to provide an overview of the character of a potential borrower at a low price. Although the application of psychometric tests evokes the issue of cultural validity *and manipulation, they create an instrumental supplement to financial and digital* data (Allen et al. 2021). Another established branch of literature underscores the significance of financial literacy in determining the outcomes of borrowing and repaying. Lusardi and Mitchell (2014) believe that literacy decreases the probability of over-indebtedness, loan terms misinterpretation, and discipline in loan repayment. Cole et al. (2011) discovered that literacy interventions in randomized control trials in India and Indonesia did have significant impacts on uptake of formal savings and enhancing loan repayment.

2.2. India-specific evidence

India presents a paradise of experimental credit scoring because of its fast-digitization and endemic financial exclusion. According to Virdi and Mer (2023), Indian fintechs use UPI transaction histories, mobile recharge data and bill payment records to issue small-ticket loans to new-to-credit customers. According to Chatterjee and Chang (2025), they come with the risks of over-indebtedness, predatory lending, and poor consumer protection. RBI (2021) has also raised concerns regarding the issue of algorithmic bias and required more strict regulation of digital lenders. Breza and Kinnan (2021) examine the microfinance crisis of 2010 that highlighted the risks of predatory lending when no adequate screening tools are in place. Benami and Carter (2021) emphasize the weakness of the conventional repayment models used in microfinance institutions, and they propose new methods to be implemented and refer to behavioral and digital data. Formal credit histories are also a binding factor to MSMEs: Miriam et al. (2017) estimated that the MSME credit gap in India was USD 330 billion. This shortfall in financing can be filled in by alternative data. Psychometric research on India is very scarce yet promising. Gupta and Arora (2020) show that conscientiousness and internal locus of control have a positive correlation with repayment of Indian MSME borrowers. On literacy, the situation is more evident: according to surveys, less than 3 out of 5 Indian adults can comprehend the simple interest compounding (Hilpisch 2020). The framework provided by Lusardi and Mitchell (2014) implies that this gap is directly converted into repayment risks, which supports the argument of including literacy in credit risk models.

2.3. Gaps in resarch

Even with the increasing amount of research on alternative credit assessment methods, there are still significant gaps that need to be addressed. Existing studies primarily focus on digital footprints, psychometric attributes, and financial literacy as separate factors influencing creditworthiness, often overlooking how these elements might work together. As a result, there are not many thorough models that bring together these aspects to give a clearer picture of how borrowers behave with credit. Secondly, in the Indian context, a significant portion of the evidence available comes from proprietary fintech datasets that are not publicly accessible, or from studies that depend on secondary data and small-scale experiments. Consequently, there is a lack of extensive primary research exploring how borrower characteristics relate to actual loan performance. Third, there is a lack of thorough comparative analysis between alternative credit-scoring methods and traditional bureau-based models. There have been limited studies that thoroughly examine if alternative indicators can serve as effective substitutes for traditional credit scores, or if they hold more value as additional tools within mixed scoring systems. Fourth, the current literature offers only a narrow view of the variations in credit assessment across different segments, especially when it comes to the distinctions between urban and rural borrowers, individual and MSME borrowers, and populations spread across various geographical areas. Ultimately, while issues surrounding fairness, transparency, algorithmic bias, and data privacy are often highlighted in discussions about alternative credit scoring, the regulatory and ethical aspects have mostly been explored in theory and lack strong empirical support. Consequently, more empirical research is needed to evaluate how different credit assessment models affect financial inclusion, all while ensuring adherence to regulations, transparency, and the protection of consumers. Filling these gaps would help create credit assessment frameworks that are more inclusive, accurate, and responsible. Research suggests that there are various alternative indicators, such as digital behaviours, psychometric traits, and financial literacy, which can significantly predict creditworthiness, especially in cases where credit histories are limited. In India, fintech innovation has rapidly outpaced academic examination, creating a clear need for systematic and empirical validation using primary data. The upcoming research aims to address this gap by creating a comprehensive data set and evaluating the predictive validity of various alternative and hybrid credit scoring models (Vardari & Sood, 2026).

2.4. Theoretical framework

The present study draws on four related theories: Information Asymmetry Theory, Signaling Theory, Behavioral Finance Theory and Fintech Adoption Theory. These frameworks together account for the potential of using alternative data sources to enhance credit assessments and increase financial inclusion for those who do not have a traditional credit history.

2.4.1. Information asymmetry theory

The principle of asymmetric information emphasises the examination of loan access and repayment behaviour, wherein the lender cannot ascertain the quality of the borrower (Akerlof 1970). Stiglitz and Weiss (1981) demonstrated in their foundational work that credit markets may fail to equilibrate due to adverse selection and moral hazard, resulting in credit rationing instead of elevated interest rates. This results in the exclusion of high-risk, unknown borrowers who lack a repayment history or collateral, which constitutes a fundamental issue in emerging economies. Researchers in behavioural economics and psychology have indicated that borrower reliability is determined not only by income and assets but also by non-cognitive traits such as conscientiousness, time preference, and locus of control (Heckman et al. 2006; Borghans et al. 2008). These characteristics influence discipline, planning, and risk-taking, therefore affecting the capacity to repay. Creditworthiness can be conceptualised as a multidimensional construct comprising economic, behavioural, and psychological elements. Furthermore, information economics suggests that the efficacy of financial markets depends on the availability of information to investors (Varian 2014). Broader data, including digital transaction footprints and psychometric assessments, might mitigate information asymmetry, reduce default rates, and enhance financial inclusion. This provides the theoretical rationale for employing alternate data in credit assessment (Khandker and Koolwal 2016).

2.4.2. Signaling theory

Signaling Theory states that there is information being communicated in the visible behaviour, and that this information is related to the invisible characteristics (Spence 1973). Positive behaviors, like paying bills on time, making regular UPI transactions and making regular digital financial transactions could represent responsibility, self-discipline and repayment capacity in the context of digital finance. These digital signals offer lenders additional data that could help in making a credit decision – especially when a potential borrower doesn't have a thick file.

2.4.3. Behavioral finance theory

Behavioral Finance Theory highlights that psychological qualities have an effect on financial decisions, beyond economic ones (Kahneman and Tversky 1979). Borrowing behaviour, repayment discipline and financial decision making are moulded by such traits as conscientiousness, risk tolerance and locus of control. Those with more conscientiousness tend to be more organized, more financially disciplined, while being more prone to risk-taking could also lead to over-borrowing and repayment problems.

2.4.4. Fintech adoption theory

Fintech Adoption Theory is the theory that predicts valuable behavioural data that can be generated from the adoption and use of digital financial services by individuals (Davis 1989; Venkatesh et al. 2003). With the growing use of digital payment platforms, mobile banking apps, and online financial services by consumers, they leave behind digital traces that can be used for alternative credit assessment. This can lead to improvements in credit access, financial inclusion and improved risk assessment, all of which are possible with the help of fintech-enabled data ecosystems.

2.5. Hypotheses development

Based on the theoritical framework, the following hypotheses are proposed:

H_1 *When UPI transactions are higher, the likelihood of a loan default is lower.*
H_2 *The pattern of timely bill payment is negatively related to the risk of loan default.*
H_3 *Higher DFI scores are correlated with lower risk of loan default.*
H_4 *Loan default risk is negatively correlated with conscientiousness.*
H_5 *The greater the risk tolerance, the higher the risk of default on the loan.*
H_6 *The risk of loan default is negatively related to financial literacy.*
H_7 *Combining digital behavioral indicators, psychometric attributes and financial literacy measures enhances prediction over traditional assessment methods.*

3. Data and methodology

3.1. Research design

The research presented is a cross-sectional survey design that utilises primary data collected in India between January and April 2024. The survey gathers information about borrowers, focusing on their demographics, financial capabilities, digital habits, psychological traits, and understanding of financial concepts. The study holds potential value by providing empirical evidence on the predictive power of alternative credit scoring indicators in India, a topic that is seldom explored. It connects these variables to self-reported loan outcomes, such as approval and default within a 12-month period. A structured questionnaire was utilised, administered through both online and offline formats to ensure a broader reach across various groups. Throughout the data collection process, 550 individuals were approached. After a thorough screening process to ensure completeness, consistency, and eligibility, we retained 400 valid responses for final analysis, resulting in an effective response rate of 72.7%. The eligibility criteria required respondents to be at least 18 years old and to have some prior borrowing experience. Questionnaires with significant missing data (over a third) or inconsistencies were excluded from the final data set.

Three factors played a role in the decision to choose a primary survey. Firstly, proprietary fintech data cannot be shared with academic researchers due to confidentiality concerns. Secondly, data that is publicly accessible, such as the World Bank Findex, does not include information on loan outcomes. Third, primary data allows for the simultaneous collection of digital, psychometric, and literacy indicators, resulting in a multidimensional framework that captures the intricate nature of credit evaluation.

3.2. Assessing data quality, reliability and validity

A number of steps, as shown in Table 1 were implemented to ensure the quality of the data and the dependability of the measures. A pilot study was carried out with 30 participants to evaluate the clarity, content validity, and relevance of the questionnaire prior to the main data collection. A survey tool was created based on input from participants in the pilot phase.

Table 1. Data quality, reliability and validity

Assessment procedure	Statistical technique	Acceptance criteria	Outcome
Pilot Testing	Pre-test conducted with 30 respondents	Instrument comprehensibility and relevance	Feedback incorporated to refine questionnaire items and enhance content validity
Internal Consistency Reliability	Cronbach's Alpha	$\alpha \geq 0.70$	All constructs demonstrated satisfactory reliability
Construct Validity	Exploratory Factor Analysis (EFA)	Factor loadings ≥ 0.50	Construct validity established for all measurement scales
Sampling Adequacy	Kaiser-Meyer-Olkin (KMO) Measure	KMO ≥ 0.60	Sampling adequacy confirmed for factor analysis
Factorability Assessment	Bartlett's Test of Sphericity	$p < 0.001$	Correlation matrix suitable for factor extraction
Missing Data Treatment	Listwise Deletion	Minimal missing observations	No material impact on subsequent analyses
Data Screening and Cleaning	Removal of duplicate and incomplete responses	Valid and complete responses retained	Improved overall data quality and analytical accuracy

The internal consistency was assessed using Cronbach's alpha coefficients. The reliability of all constructs was strong, with values exceeding the recommended threshold of 0.70. Exploratory factor analysis was employed to assess the construct validity. The Kaiser-Meyer-Olkin (KMO) statistic exceeded the accepted threshold of 0.60, and Bartlett's Test of Sphericity showed significance, indicating that the data was suitable for factor analysis. There was hardly any missing data, and it was handled through listwise deletion. During the data cleaning process, we removed duplicate entries and incomplete responses.

3.3. To create the Digital Footprint Index (DFI)

To measure the level of engagement with digital financial services and online financial activities, a Digital Footprint Index (DFI) was created. Five dimensions of the observed digital financial behaviors were used in the making of the index.

Table 2. Digital Footprint Index (DFI)

Indicator	Weight (%)
UPI transaction frequency	25
Bill payment timeliness	25
Mobile recharge regularity	20
E-commerce transaction activity	20
Digital financial platform usage	10

Table 2 presents the weighting scheme used to construct the Digital Footprint Index (DFI). Greater weights were assigned to UPI transaction frequency and bill payment timeliness because previous studies identify these variables as the strongest indicators of repayment behaviour. Moderate weights were assigned to mobile recharge regularity and e-commerce activity, while digital financial platform usage received the lowest weight because it primarily reflects technology adoption rather than repayment discipline.

To ensure comparability across indicators, all variables were normalized and transformed onto a common scale prior to aggregation. The Digital Footprint Index (DFI) was constructed as a weighted composite measure that captures the extent of an individual's digital financial engagement. The index was calculated using the formula shown in Equation 1 below:

$$\text{DFI} = \sum i = 1 \text{n} w_i X_i \tag{1}$$

3.3.1. Justification for DFI weighting

The weighting structure of the Digital Footprint Index (DFI) was developed based on theoretical evidence from the alternative credit-scoring literature and validated using exploratory statistical analysis. Indicators directly reflecting financial discipline and repayment-related behaviour, namely UPI transaction frequency and bill payment timeliness, were assigned higher weights (25% each) because previous studies identify them as strong predictors of creditworthiness (Berg et al. 2020; Jagtiani and Lemieux 2018). Mobile recharge regularity and e-commerce activity were assigned moderate weights (20% each), while digital financial platform usage received a lower weight (10%) because it primarily captures technology adoption rather than actual repayment behaviour.

To further validate the weighting scheme, an Exploratory Factor Analysis (EFA) was conducted on the five DFI indicators. The factor-loading results showed that UPI transaction frequency (loading = 0.82) and bill payment timeliness (loading = 0.79) exhibited the strongest association with the latent digital financial behaviour construct. Mobile recharge regularity (loading = 0.71) and e-commerce activity (loading = 0.68) demonstrated moderate contributions, whereas digital financial platform usage recorded the lowest loading (0.51). These findings provide empirical support for assigning relatively higher weights to transaction-based indicators and lower weights to platform usage variables.

In which the value of the assigned weight w_i is multiplied by the normalized value X_i of the indicator. The Index had a range of 0 to 1, with higher scores representing more digital financial engagement. The reliability and validity of the index were assessed using appropriate statistical techniques to ensure the robustness and consistency of the measurement framework. The validated index was subsequently employed as a key explanatory variable in the analysis of borrowers' creditworthiness and loan performance.

3.4. Sampling strategy

This study employed a stratified sampling approach to ensure adequate representation across geographical locations and borrower categories. Stratification was undertaken to capture heterogeneity in borrowing behavior and digital financial engagement among different segments of the Indian population. A total sample of 400 respondents was targeted. Of these, 220 respondents were drawn from major urban centers, including Delhi, Mumbai, Bengaluru, and Hyderabad, while 180 respondents were selected from rural areas across the states of Uttar Pradesh, Bihar, Maharashtra, and Tamil Nadu. This distribution enabled the study to compare digital financial behaviors and credit outcomes across urban and rural contexts. The sample comprised two primary borrower categories. Individual borrowers accounted for 240 respondents and included both salaried and self-employed individuals. The remaining 160 respondents were owners of Micro, Small, and Medium Enterprises (MSMEs) operating in sectors such as retail trade, services, and agriculture. The inclusion of both individual and business borrowers facilitated a broader assessment of alternative credit-scoring mechanisms across diverse credit markets. To be eligible for participation, respondents were required to have applied for a loan, either through formal financial institutions or informal lending channels, within the previous two years. Both approved and rejected applicants were included in the sample to minimize selection bias and to ensure variation in credit outcomes. This approach enabled the study to examine the relationship between borrower characteristics, alternative credit indicators, and loan approval and repayment performance.

Respondents were selected using purposive and convenience sampling techniques to ensure representation from digitally active borrowers. Data were collected using a structured questionnaire administered through both Google Forms and face-to-face surveys. The online survey link was distributed through digital channels, while face-to-face surveys were conducted at bank branches, business centers, and public locations to reach respondents with varying levels of digital engagement.The survey targeted individuals who had: Used UPI within the last six months, Applied for a loan within the previous three years, Used at least one digital financial service. Prior to full deployment, a pilot study involving 30 respondents was conducted to test questionnaire clarity and reliability. result of Cronbach's Alpha = 0.84. Necessary modifications were made based on participant feedback. Data collection resulted in 438 responses. After removing incomplete questionnaires and inconsistent entries, 400 usable responses remained for analysis. Participation was voluntary, anonymous, and based on informed consent.

3.5. Survey instrument and data collection

Primary data were collected using a structured questionnaire designed to capture information on respondents' demographic characteristics, digital financial behavior, psychometric attributes, financial literacy, and loan outcomes. The questionnaire consisted of five sections.

The first section gathered demographic and socioeconomic information, including age, gender, educational attainment, occupation, monthly income, household savings rate, loan amount, and applicable interest rate. The second section measured digital behavior indicators that constituted the Digital Footprint Index. These indicators included the frequency of monthly UPI transactions, frequency of e-commerce purchases, timeliness of bill payments, regularity of mobile phone recharges, and consistency in the use of digital financial platforms. Responses were standardized and aggregated to construct a composite Digital Footprint Index ranging from 0 to 1, with higher values indicating greater digital financial engagement. The third section assessed psychometric traits using validated short-form scales. Conscientiousness was measured using items adapted from the Big Five personality framework, while locus of control was assessed using a modified version of the Rotter Index. Risk tolerance was measured through a five-point Likert scale capturing respondents' willingness to engage in financial risk-taking.

The fourth section evaluated financial literacy using a five-item test adapted from the framework developed by Lusardi and Mitchell (2014). The questions covered fundamental financial concepts, including simple interest, compound interest, inflation, diversification, and loan EMI calculations. Respondents received a score ranging from 0 to 5 based on the number of correct responses. The final section captured loan outcomes. Respondents reported whether their most recent loan application had been approved or rejected and whether they had experienced loan default during the previous twelve months. A respondent was classified as a defaulter if three or more consecutive loan repayments had been missed or if the lending institution had formally categorized the borrower as being in default. Ethical approval for this questionnaire-based study was obtained from *Chandigarh University* prior to data collection.

Prior to the main survey, a pilot study involving 30 respondents was conducted to assess the clarity, relevance, and reliability of the questionnaire. Based on participant feedback, minor modifications were made to improve item wording and comprehension. Reliability analysis indicated satisfactory internal consistency, with Cronbach's alpha values ranging from 0.72 to 0.81 for the psychometric constructs, exceeding the recommended threshold of 0.70.

3.6. Variable specification

The study employed in Table 3, two *dependent variables*: loan approval and loan default. Loan approval was measured as a binary variable, where 1 indicated an approved loan application and 0 indicated a rejected application. Loan default, the primary outcome variable, was also measured as a binary variable, where 1 represented a borrower who had defaulted on loan repayments and 0 represented regular repayment behavior.

Table 3. Identified variables

	Dependent Variables	
Variable	**Measurement Definition**	
Loan Approval	Binary variable (1 = Approved, 0 = Rejected)	
Loan Default	Binary variable (1 = Default, 0 = Regular Repayment)	
	Independent Variables	
Domain	**Variables (Measurement)**	**Expected Effect on Default**
Demographics	Age (years), Gender (1=female), Education (years)	Ambiguous
Economic capacity	Monthly income (₹), Savings rate (%), Loan size (₹), Interest rate (%)	Higher income → ↓ default; higher loan/interest → ↑ default
Digital behaviors	UPI transactions/month, Bill payment timeliness (0–1), E-commerce activity (0–1), Mobile top-ups/month, Digital footprint index	Higher digital discipline → ↓ default
Psychometrics	Conscientiousness (1–5), Locus of control (1–5), Risk tolerance (1–5)	Conscientiousness, internal locus → ↓ default; high risk tolerance → ↑ default
Financial literacy	Literacy score (0–5)	Higher literacy → ↓ default
Traditional credit	Bureau score (500–850, where available)	Higher score → ↓ default

The *independent variables* were categorized into six domains. *Demographic variables* included age, gender, and education. *Economic capacity variables* comprised monthly income, savings rate, loan size, and interest rate. Digital behavior variables included UPI transaction frequency, bill payment timeliness, e-commerce activity, mobile top-up frequency, and the Digital Footprint Index. *Psychometric variables* consisted of conscientiousness, locus of control, and risk tolerance. Financial literacy was measured using a score ranging from 0 to 5 based on respondents' understanding of key financial concepts. Finally, *traditional creditworthiness* was captured through the borrower's credit bureau score, where available. Higher levels of income, savings, digital financial engagement, conscientiousness, internal locus of control, financial literacy, and bureau credit scores were expected to reduce the likelihood of loan default, whereas larger loan sizes, higher interest rates, and greater risk tolerance were expected to increase default risk.

3.7. Econometric model

The relationship between alternative indicators and loan default was estimated using a binary logistic regression model as shown in Equation 2:

$$Logit(P\_i) = ln\left(\frac{P_i}{1-P_i}\right) = \beta_0 + \beta_1 X_{(econ,i)} + \beta_2 X_{(digital,i)} + \beta_3 X_{(psych,i)} + \beta\_4\, X\_(literacy, i) + \beta\_5\, X\_(bureau, i) + \varepsilon_i \tag{2}$$

Where:
Pi = Probability that borrower $i$defaults on a loan

- $ln\left(\frac{P_i}{1-P_i}\right)$= *probability of default for borrower iii*
- *XeconX_{econ}Xecon = economic capacity variables*
- *XdigitalX_{digital}Xdigital = digital behavior indicators*
- *XpsychX_{psych}Xpsych = psychometric traits*
- *XliteracyX_{literacy}Xliteracy = financial literacy score*
- *XbureauX_{bureau}Xbureau = traditional bureau score*

To assess the predictive value of alternative credit indicators, two logistic regression models were estimated (Gelman and Hill 2007). Model A (Alternative Credit Model) included economic, digital behavior, psychometric, and financial literacy variables but excluded traditional bureau scores. This model evaluated the standalone predictive power of alternative indicators in explaining loan default. Model B (Hybrid Credit Model) incorporated all variables in Model A along with the traditional bureau credit score. The comparison of these two models enabled an assessment of whether alternative credit indicators can complement or potentially substitute conventional credit-scoring measures in predicting borrower default risk.

3.5. Robustness checks

To evaluate the stability and reliability of the empirical findings, several robustness checks were conducted. Initially, subsample analyses were performed by estimating distinct logistic regression models for urban and rural borrowers, in addition to individual borrowers and MSME owners. This allowed for an analysis of how the connections between the explanatory variables and loan default varied among different borrower segments. Next, exclusion tests were conducted by re-evaluating the regression models after removing income-related variables. These tests aimed to assess how well digital behaviour indicators, psychometric traits, and financial literacy measures can independently predict default risk.

Third, we looked into interaction effects to see if financial literacy plays a role in moderating the connection between digital behaviour and loan default. Interaction terms between the Digital Footprint Index and financial literacy scores were included in the regression models to evaluate possible moderating effects. Finally, we assessed the predictive performance of the estimated models through Receiver Operating Characteristic (ROC) curve analysis. The Area Under the Curve (AUC) was calculated for both the Alternative Credit Model (Model A) and the Hybrid Credit Model (Model B). A comparison of the AUC values showed how effective different credit indicators are and their added value beyond traditional credit bureau scores when it comes to predicting loan defaults.

To ensure confidentiality and privacy, all responses were anonymized and stored securely, with no personally identifiable information retained in the final dataset. Given the sensitive nature of financial and psychometric information, appropriate data protection measures were implemented throughout the research process.

4. Result analysis

4.1. Descriptive statistics

Table 4 shows the descriptive statistics for a sample of 400 respondents. The average respondent was 34.2 years old, and females made up 45% of the sample. The respondents showed average levels of income, financial literacy, and digital financial engagement, indicated by a mean Digital Footprint Index score of 0.61. The average bureau score among respondents with available credit records was 635.2. Regarding credit outcomes, 75% of loan applications received approval, whereas 15% of borrowers indicated that they defaulted on their loans. The statistics show that most respondents were young adults with moderate incomes and a strong level of digital engagement.

Table 4. The key descriptive statistics for the sample of 400 respondents

Variable	Mean	Std. Dev.	Min	Max
Age (years)	34.2	8.6	20	59
Gender (1=Female)	0.45	0.49	0	1
Education (years)	11.4	3.2	0	18
Monthly Income (₹ ‘000)	40.1	18.7	8	95
Savings Rate (%)	18.2	7.4	0	45
Loan Size (₹ ‘000)	68.7	30.2	10	200
Interest Rate (%)	12.8	3.9	7	24
UPI Transactions (per month)	28.4	12.6	5	70
Bill Payment Timeliness (0–1)	0.82	0.15	0.3	1
Mobile Top-ups (per month)	6.7	3.4	1	15
Digital Footprint Index (0–1)	0.61	0.22	0.1	1
Conscientiousness (1–5)	3.4	0.9	1	5
Locus of Control (1–5)	3.1	1.0	1	5
Risk Tolerance (1–5)	2.9	1.1	1	5
Financial Literacy Score (0–5)	2.9	1.2	0	5
Bureau Score (500–850, n=200)	635.2	74.6	510	810
Loan Approved (1=yes)	0.75	0.43	0	1
Default (1=yes)	0.15	0.36	0	1

4.2. Results of logistic regression

Table 5 presents the regression findings of Model A (Alternative-only) and Model B (Hybrid including bureau scores). The dependent variable (Loan repayment performance) is binary in nature thus logistic regression was used. This technique has been widely used in the field of credit risk assessment because it is easily interpretable and can be used to estimate default probabilities (Hosmer et al. 2013).

The results show that larger *loan sizes* significantly increase the likelihood of default in both models. Among the *digital behavior variables*, UPI transaction frequency, bill payment timeliness, and the Digital Footprint Index are negatively associated with default risk, indicating that borrowers with stronger digital financial engagement are less likely to default. Bill payment timeliness emerges as the strongest predictor, with an odds ratio of 0.10 in Model A and 0.12 in Model B. Regarding *psychometric* characteristics, conscientiousness significantly reduces default risk, whereas risk tolerance increases the probability of default. *Financial literacy* also exhibits a significant negative relationship with loan default, suggesting that financially knowledgeable borrowers demonstrate better repayment behavior. In Model B, bureau score is negatively associated with default risk, indicating that borrowers with stronger credit histories are less likely to default. However, the continued significance of digital, psychometric, and financial literacy variables highlights the complementary role of alternative credit indicators beyond traditional credit scores. Model performance improves with the inclusion of bureau scores, as reflected by the increase in Pseudo-(R^2) from 0.29 to 0.36. Similarly, the Area Under the Receiver Operating Characteristic Curve (AUC) increases from 0.78 in Model A to 0.84 in Model B, indicating superior predictive accuracy of the hybrid model.

Table 5. Logistic regression models of loan default

Variable	Model A OR	Model B OR
Loan Size	1.52***	1.44***
Interest Rate	1.08	1.05
UPI Transactions	0.94**	0.95**
Bill Payment Timeliness	0.10***	0.12***
Mobile Top-ups	0.91*	0.93
Digital Footprint Index	0.22***	0.25***
Conscientiousness	0.67**	0.69**
Locus of Control	0.88	0.91
Risk Tolerance	1.39**	1.32**
Financial Literacy Score	0.74***	0.71***
Bureau Score (per +50 pts)	–	0.67***
Constant	1.05	0.98
N	400	200
Pseudo-R^2	0.29	0.36

*p<0.1, **p<0.05, ***p<0.01

The subsample analysis indicates heterogeneity in the determinants of loan default across borrower groups. UPI transaction frequency and e-commerce activity were stronger predictors among urban borrowers, whereas bill payment timeliness and mobile top-up frequency were more influential among rural borrowers. For MSME owners, risk tolerance emerged as a significant determinant of default risk, while conscientiousness and financial literacy were stronger predictors among individual borrowers.

4.3. ROC curve analysis

This proves that the hybrid models are more precise, although alternative-only models still can be used when data on the bureau is unavailable.

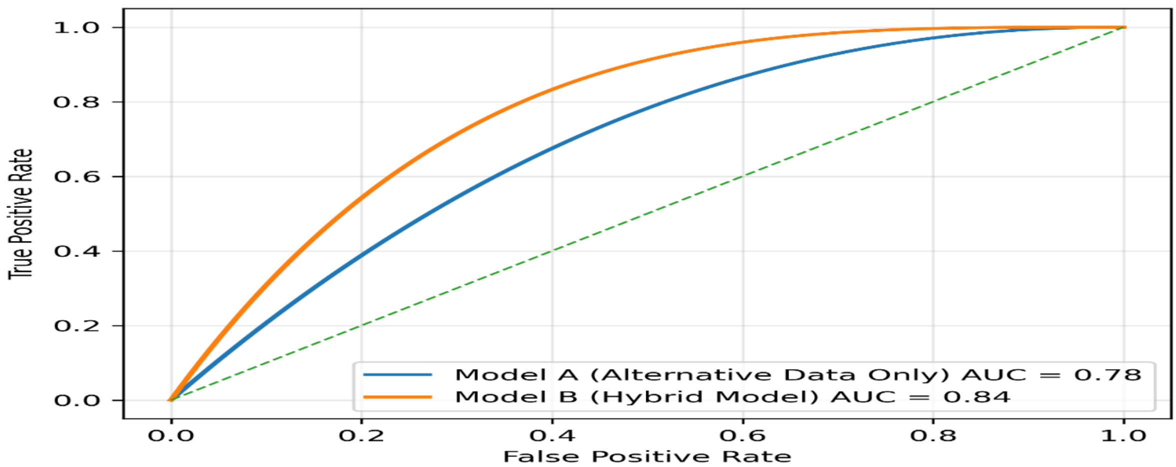

Figure 1. ROC curves of Model A vs B

Figure 1 compares the ROC curves of the Alternative Credit Model and the Hybrid Credit Model. The Hybrid Model achieved an AUC of 0.84 compared with 0.78 for the Alternative Model, indicating superior predictive accuracy. Nevertheless, the Alternative Model also demonstrated acceptable discrimination, suggesting that alternative credit indicators can effectively predict default risk even when bureau scores are unavailable.

4.4. Behavioral predictors

The effect of behavioral predictors on default risk is pictured in Figure 2 and Figure 3. Figure 2 shows that borrowers who pay their bills on time (1.0) have a low probability of default (below 5%), whereas borrowers with lower levels of payment timeliness exhibit a substantially higher default probability, reaching approximately 25%. Figure 3 illustrates that borrowers who are risk-takers have a default probability greater than 25, whereas risk-averse borrowers have a default probability below 10.

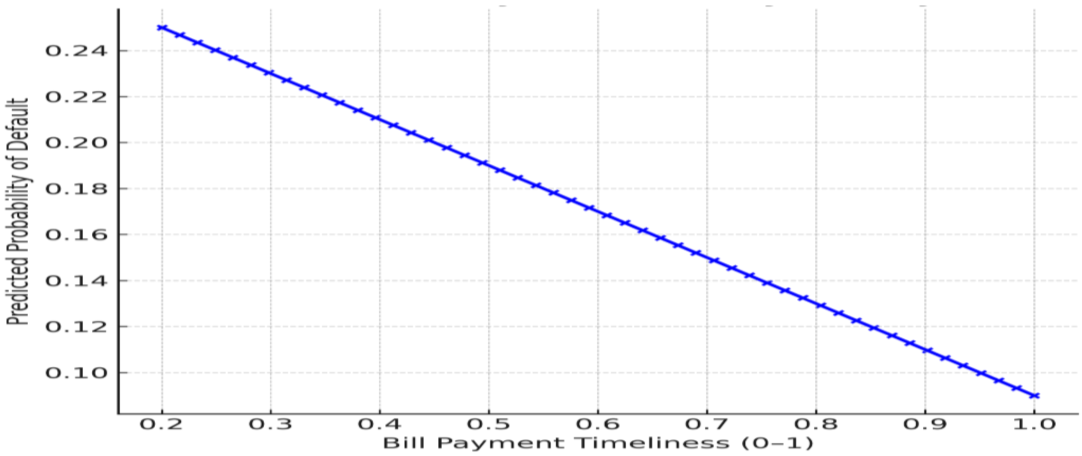

Figure 2. Relationship between bill payment timeliness and the predicted probability of loan default

Figure 2 illustrates the relationship between bill payment timeliness and the predicted probability of loan default. Borrowers who consistently paid bills before the due date exhibited substantially lower predicted default probabilities than those with poor payment discipline, highlighting the importance of timely payment behaviour in alternative credit assessment.

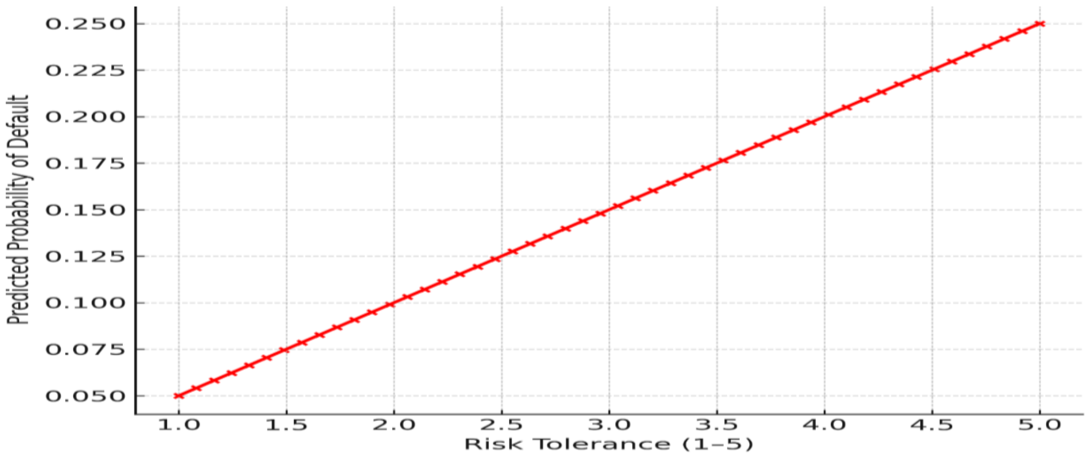

Figure 3. Relationship between risk tolerance and predicted loan default probability

Figure 3 shows the relationship between risk tolerance and predicted loan default probability. As risk tolerance increases, the estimated probability of default also increases, suggesting that borrowers with greater willingness to take financial risks are more likely to experience repayment difficulties.

4.5. Robustness checks

The robustness checks validated the consistency of the findings. When we re-estimated the models without including income-related variables, we found that digital behaviour and psychometric indicators still held statistical significance, highlighting their ability to predict outcomes independently. The analysis of interactions showed that financial literacy plays a role in how digital behaviour affects default risk. Borrowers who are active online tend to have lower chances of defaulting when they possess higher levels of financial literacy. Additionally, changing the definition of default to two missed payments in a row instead of three yielded results that were qualitatively similar. Ultimately, the diagnostics for multicollinearity showed that all variables had Variance Inflation Factor (VIF) values under 2.5, suggesting that there are no significant issues with multicollinearity.

5. Findings and discussions

The analysis shows that digital behaviors, psychometric characteristics, and financial literacy are statistically meaningful and significant economic predictors of loan default. Of these, bill payment timeliness was the most powerful single predictor, with the lowest and highest categories representing a reduction in the default risk by nearly 90%. This highlights the importance of behavioral discipline cues, even low value, high frequency behavior (such as payment of utility on time) is a proxy of repayment reliability. Likewise, psychometric predictors, especially conscientiousness and risk tolerance were strong predictors. The conscientiousness (diligence and planning) is consistent with the repayment discipline; the higher risk tolerance was also associated with the higher default risk, which is in line with the hypothesis that risk-seeking borrowers are more likely to overextend themselves financially. These results attest to the promise of character-based tests when it comes to thin-file situations. There was also the central role of financial literacy. Those who got higher points on the 5-item quiz were much less likely to default as borrowers. This is in line with the fact that informed borrowers are more aware of loan obligations, estimate EMI affordability, and they tend not to over-borrow. Notably, literacy was not only a direct way of decreasing default but also a moderator of the impact of digital behaviors, which emphasizes its complementary role in determining the outcome of repayments.

Highest predictive power (AUC = 0.84) was achieved with hybrid models that were based on combination of bureau scores with other indicators. Nevertheless, other alternative-only models (AUC = 0.78) were good enough to offer a plausible risk assessment instrument in the case of thin-file borrowers. This implies that traditional scores are not completely substituted by alternative data though this does not apply fully at least in Indian context. The findings are highly correlated with credit rationing theory (Stiglitz and Weiss 1981) which estimates that risk-unknowen borrowers are shut out in information-poor markets. Digital and psychometric variables minimize information asymmetry by complementing other signals and allowing the lenders to price risk more efficiently and lend to locked-out populations. Under the behavioral economics view, conscientiousness and literacy can be regarded as important factors that prove the thesis that financial decision-making is influenced by non-cognitive traits and knowledge rather than monetary capacity. The results confirm the conceptualization of creditworthiness that is multidimensional and developed in personality economics (Heckman et al. 2006). Lastly, regarding information economics, the enhancement of predictive power in a combination with bureau and alternative data demonstrates the idea by Ozkan et al. (2014) that the wider information set is, the more efficient it becomes. Lenders will also be able to minimize Type I (false approvals) and Type II (false rejections) errors to enhance portfolio quality and financial inclusion at the same time.

The results of this study go well with the global research on alternative credit scoring. The important role of digital behaviour indicators, especially UPI transaction activity and the punctuality of bill payments, reinforces previous findings that transactional digital footprints can reliably forecast credit risk in conjunction with traditional credit variables (Berg et al. 2020; FSD Kenya 2019). In a similar vein, the results concerning psychometric traits are consistent with the findings of Karlan and Zinman (2010) and Klinger et al. (2013), who highlighted conscientiousness and locus of control as key predictors of repayment behaviour in developing economies. The current study broadens this evidence within the Indian context, enhancing the cross-country validity of psychometric credit assessment. Additionally, the negative link between financial literacy and loan default aligns with previous studies (Lusardi and Mitchell 2014; Cole et al. 2011), while also emphasising how financial literacy can enhance the predictive power of digital behaviour indicators. Even with these similarities, significant contextual differences become apparent. In contrast to studies in countries like China that highlight social media activity and e-commerce behaviour as important indicators for alternative credit, the situation in India focuses more on the usage of UPI and the punctuality of bill payments. This difference highlights the distinct features of India's Digital Public Infrastructure (DPI) ecosystem and indicates that the success of alternative credit indicators is influenced by the local digital and institutional contexts. As a result, the findings highlight how crucial it is to tailor credit-scoring models to the specific contexts of different countries.

5.1. India-specific insights

The context of digital finance in India is particularly significant when it comes to alternative credit risks. The rise of UPI, Aadhaar-enabled authentication, Jan Dhan financial inclusion initiatives, and the Account Aggregator framework has generated a significant amount of digital transaction data that can be leveraged to facilitate responsible lending. The adoption of digital public infrastructure in India opens up exciting opportunities to integrate alternative data into credit scoring, helping to extend financial inclusion to underserved groups, which sets it apart from many other developing economies.

6. Implications of study

6.1. Theoretical implications

The study significantly contributes to the existing body of knowledge on alternative credit scoring by illustrating that the concept of creditworthiness extends beyond conventional financial records. It reveals that a comprehensive understanding of an individual's creditworthiness can be effectively captured through an analysis of digital behaviour, psychometric characteristics, and financial literacy. Unlike previous studies that have often looked at these dimensions separately, the current research brings them together within a cohesive framework, offering a deeper insight into borrower risk (Demirgüç-Kunt et al. 2022). The findings indicate that alternative indicators hold considerable explanatory power, even when conventional bureau scores are taken into account. This suggests that these indicators reveal behavioural and cognitive aspects of creditworthiness that traditional credit assessment systems often overlook.

The study makes a significant addition to the present discussion related to financial inclusion, emphasising the potential of alternative data to bridge the information gap that often exists between lenders and borrowers. The findings especially strengthen the argument that digital footprints and behavioural indicators can effectively act as reliable proxies for assessing repayment capacity in individuals who possess limited or no credit histories (Chen et al. 2019). This perspective invites a reevaluation of traditional credit assessment methods in light of evolving digital landscapes. Moreover, the variations noted among urban, rural, MSME, and individual borrower categories indicate that credit risk is inherently influenced by context and cannot be comprehensively assessed through uniform models alone (Banerjee and Duflo 2014). This finding significantly improves our knowledge of credit risk assessment by highlighting the critical role of borrower diversity and the influence of local digital ecosystems in shaping predictive relationships. Eventually, this study plays a significant role in the ongoing discussions surrounding the future of data-driven lending, offering valuable insights drawn from India's swiftly changing digital financial landscape. The findings indicate that the effectiveness of alternative data in predicting outcomes is shaped by both institutional and technological environments (Fenwick et al. 2020). This not only deepens the international knowledge regarding the issue but also points to the necessity for customised approaches in credit scoring research risk. The findings indicate that alternative indicators hold considerable explanatory power, even when conventional bureau scores are taken into account. This suggests that these indicators reveal behavioural and cognitive aspects of creditworthiness that traditional credit assessment systems often overlook (Prasad 2021).

While the findings provide important insights about role of alternative credit indicators in predicting loan repayment performance, there are certain limitaions too. The study is based on cross sectional survey, which limits the ability to capcture changes in borrower behavuiour over the time. Further, the sample may not fuly represent the diversity of borrowers across different regions and lending contexts in India. The future study may compare traditional statistical approaches with machine learning and AI models to enhance alternative credit assessment and support financial inclusion.

6.2. Policy implications

The findings of this study have important implications for lenders, fintech companies, and policymakers. The results show that simple digital behavior indicators, such as bill payment timeliness, UPI transaction frequency, and digital footprint scores, can provide valuable insights into borrowers' repayment capacity. Since these indicators are generated through routine financial activities, they provide a cost-effective and timely source of information for credit assessment. The study also demonstrates that combining alternative indicators with traditional bureau scores produces better predictive performance than relying on conventional credit information alone. This suggests that lenders can improve credit risk assessment by adopting hybrid scoring models that integrate both traditional and alternative data sources. Such models are particularly useful for evaluating thin-file borrowers who lack extensive credit histories and are often excluded from formal financial systems. Another important implication relates to borrower segmentation. The findings reveal that the factors influencing repayment behavior differ across urban and rural borrowers as well as between MSME owners and individual borrowers. Consequently, lenders may achieve better credit decisions by developing tailored scoring models that reflect the characteristics and behaviors of specific borrower groups rather than applying a single standardized framework.

However, the growing use of digital and behavioral data also raises concerns regarding privacy, transparency, and fairness. It is crucial for financial institutions and fintech companies to pay attention to the explainability and responsibility of AI systems, in order to maintain transparency, fairness, and non-discrimination of alternative credit scoring models. These measures can enhance public confidence and contribute to the overall goals of financial inclusion and sustainable digital finance. Policymakers and regulators should therefore encourage responsible use of alternative data by establishing clear guidelines on data governance, consumer consent, model transparency, and bias monitoring. Such measures can help ensure that alternative credit-scoring systems expand access to finance while protecting borrower interests and maintaining trust in the financial system.

7. Conclusion

This study examined the role of digital behavioral indicators, psychometric traits, and financial literacy in predicting loan repayment performance in India. The findings reveal that alternative credit indicators, particularly bill payment timeliness, digital financial engagement, conscientiousness, and financial literacy, significantly reduce default risk, while higher risk tolerance and loan size increase the likelihood of default. Although traditional bureau scores remain important predictors, the results demonstrate that alternative indicators provide additional explanatory power and improve predictive accuracy when combined with conventional credit information. The study highlights the potential of alternative credit-scoring models to reduce information asymmetry and expand access to credit for borrowers with limited credit histories. Given India's rapidly evolving digital financial ecosystem, the integration of alternative data into credit assessment frameworks can support both financial inclusion and effective risk management. Overall, the findings indicate that using hybrid and segment-specific credit-scoring models presents a valuable opportunity for creating lending systems that are more inclusive, accurate, and responsible.

Declaration of competing interest

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

Ethical approval

Regarding the conduct of this research, an "Ethics Permission Certificate" dated 03/06/2026 and numbered CO/OSB was obtained from the Ethics Committee of the Chandigarh University.

Acknowledgments

The views expressed in this study are those of the author.

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Appendix A. Survey Form

Introduction

Dear Respondent,

This survey aims to examine how digital financial behavior, psychometric traits, financial literacy, and traditional credit indicators influence loan approval and repayment behavior. The information collected will be used solely for academic research purposes and will remain confidential. Please answer all questions honestly.

Section A: Demographic Information

1. Gender

☐ Male ☐ Female ☐ Other

2. Age (Years): __________

3. Highest Educational Qualification

☐ Primary School ☐ Secondary School ☐ Higher Secondary

☐ Graduate ☐ Postgraduate ☐ Doctorate

4. Occupation

☐ Salaried Employee ☐ Self-Employed ☐ Business Owner/MSME

☐ Student ☐ Homemaker ☐ Retired ☐ Other ______

5. Monthly Income

☐ Below Rs. 20,000 ☐ Rs. 20,001–Rs. 40,000 ☐ Rs. 40,001–Rs. 60,000

☐ Rs. 60,001–Rs. 80,000 ☐ Above Rs. 80,000

6. Area of Residence

☐ Urban ☐ Rural

Section B: Loan Experience

7. Have you applied for any loan during the last three years?

☐ Yes ☐ No

8. Was your most recent loan application approved?

☐ Yes ☐ No

9. Loan Amount (Rs.): __________________

10. Interest Rate (%): __________________

11. Have you ever missed an EMI payment?

☐ Yes ☐ No

12. Have you ever defaulted on a loan (more than 90 days overdue)?

☐ Yes ☐ No

13. Approximately what percentage of your monthly income do you save?

☐ Less than 5% ☐ 5–10% ☐ 11–20% ☐ 21–30% ☐ More than 30%

Section C: Digital Financial Behavior

14. Have you used at least one digital financial service during the last six months?

(Examples: UPI, mobile banking, internet banking, digital wallets, online bill payments, online investments, digital lending platforms, insurance apps, etc.)

☐ Yes ☐ No

15. Have you used UPI within the last six months?

☐ Yes ☐ No

Frequency Scale

1 = Never | 2 = Rarely | 3 = Monthly | 4 = Weekly | 5 = Daily

Statement	**1**	**2**	**3**	**4**	**5**
I use UPI for financial transactions.	☐	☐	☐	☐	☐
I pay utility bills through digital platforms.	☐	☐	☐	☐	☐
I recharge mobile/internet services online.	☐	☐	☐	☐	☐
I purchase products or services online.	☐	☐	☐	☐	☐
I transfer money digitally to family, friends, or businesses.	☐	☐	☐	☐	☐

Section D: Bill Payment Discipline
Agreement Scale
1 = Strongly Disagree | 2 = Disagree | 3 = Neutral | 4 = Agree | 5 = Strongly Agree

Statement	1	2	3	4	5
I pay my utility bills before the due date.	☐	☐	☐	☐	☐
I rarely incur penalties due to delayed payments.	☐	☐	☐	☐	☐
I make loan or credit card payments on time.	☐	☐	☐	☐	☐
I keep track of upcoming financial obligations.	☐	☐	☐	☐	☐

Section E: Psychometric Measures
Conscientiousness

Statement	1	2	3	4	5
I plan tasks carefully before acting.	☐	☐	☐	☐	☐
I pay close attention to details.	☐	☐	☐	☐	☐
I complete work on time.	☐	☐	☐	☐	☐
I follow through on commitments.	☐	☐	☐	☐	☐
I keep my financial records organized.	☐	☐	☐	☐	☐

Locus of Control

Statement	1	2	3	4	5
My financial success depends mainly on my own actions.	☐	☐	☐	☐	☐
Careful planning can improve my financial future.	☐	☐	☐	☐	☐
I have control over most financial outcomes in my life.	☐	☐	☐	☐	☐
Responsible financial behavior prevents many financial problems.	☐	☐	☐	☐	☐

Risk Tolerance

Statement	1	2	3	4	5
I am willing to take financial risks for higher returns.	☐	☐	☐	☐	☐
I am comfortable investing in opportunities with uncertain outcomes.	☐	☐	☐	☐	☐
I am willing to borrow for potentially profitable opportunities.	☐	☐	☐	☐	☐
I prefer high-return investments despite higher risk.	☐	☐	☐	☐	☐

Section F: Financial Literacy

Statement	1	2	3	4	5
I understand how inflation affects purchasing power.	☐	☐	☐	☐	☐
I understand how compound interest affects savings and loans.	☐	☐	☐	☐	☐
I understand the relationship between risk and return.	☐	☐	☐	☐	☐
I understand how diversification reduces investment risk.	☐	☐	☐	☐	☐
I can compare loan options based on interest rates and repayment terms.	☐	☐	☐	☐	☐
I understand how EMIs are calculated.	☐	☐	☐	☐	☐
I understand the importance of maintaining a good credit score.	☐	☐	☐	☐	☐
I feel confident in making informed borrowing decisions.	☐	☐	☐	☐	☐

Section G: Traditional Credit Information
16. Do you know your credit score (CIBIL/Experian/Equifax)?
☐ Yes ☐ No
17. If Yes, indicate your approximate credit score range
☐ Below 600 ☐ 600–649 ☐ 650–699 ☐ 700–749 ☐ 750–799 ☐ 800 and Above
18. Number of active loans currently held
☐ None ☐ One ☐ Two ☐ Three or More

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The social dimension of ESG performance and employee compensation in the digital reporting era: Panel evidence from European firms

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HIGHLIGHTS

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ABSTRACT

With the widespread adoption of digital corporate reporting and sustainability disclosures, environmental, social, and governance (ESG) performance has become a fundamental component of corporate evaluation for investors and other stakeholders. This study examines the relationship between ESG Social scores and average employee wages among large European companies. The analysis is based on an unbalanced panel dataset comprising 323 firms included in the S&P Europe 350 Index over the period 2011-2020, employing time-, industry-, and firm-fixed effects models. Firm size and capital expenditure are included as control variables, while the explanatory variables are lagged to mitigate potential endogeneity concerns. The findings indicate a negative relationship between ESG Social scores and employee wages in the time- and industry-fixed effects models, whereas the firm-fixed effects model reveals a positive and statistically significant relationship. These results suggest that firm-specific characteristics, such as corporate culture, governance structures, and long-term social sustainability practices, play a critical role in shaping employee compensation. The findings support stakeholder theory by demonstrating that stronger social ESG commitments are associated with higher employee wages. This study provides new empirical evidence on the relationship between social ESG performance and employee welfare in European firms while highlighting the growing importance of social ESG disclosures within the digital sustainability reporting environment for corporate decision-making.

1. Introduction

In the era of digitalization, the way corporate sustainability information is produced, reported, and communicated to stakeholders has undergone a profound transformation. Today, companies disclose their environmental, social, and governance (ESG) performance not only through traditional annual reports but also through digital corporate reporting systems, online sustainability reports, and

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international ESG data platforms. This digital reporting ecosystem enables stakeholders to evaluate corporate sustainability performance in a more transparent, comparable, and timely manner. Within this context, the present study focuses on European domiciled companies based on their Environmental, Social, and Governance (ESG) scores. Prior to the widespread adoption of ESG metrics, concepts such as Socially Responsible Investing (SRI) and Corporate Social Responsibility (CSR) were commonly used in the literature for evaluating firms' social responsibility. Gillan et al. (2021) provide a comprehensive overview of ESG and CSR within corporate finance and emphasize stakeholder-oriented governance as a cornerstone of modern corporate strategy.

The widespread adoption of digital ESG reporting has significantly improved investors' ability to evaluate firms' sustainability performance. Contemporary investors increasingly consider not only financial performance but also ESG indicators that are disseminated through digital reporting platforms when making investment decisions. Pedersen et al. (2021) demonstrate that companies with superior ESG performance are preferred by ESG-conscious investors, thereby influencing equilibrium asset prices and corporate decision-making. ESG reflects a firm's commitment to environmental, social, and governance practices while simultaneously strengthening corporate reputation and stakeholder trust. Likewise, Dyck et al. (2019) show that institutional investors play a significant role in encouraging firms to adopt stronger corporate social responsibility practices worldwide.

European sustainability policies have also accelerated the digital transformation of corporate sustainability reporting. The Corporate Social Responsibility policy introduced by the European Commission in 2011 initiated a process aimed at promoting more systematic sustainability reporting. Subsequently, regulations such as the Non-Financial Reporting Directive (NFRD), the Sustainable Finance Disclosure Regulation (SFDR), and the EU Taxonomy Regulation have encouraged companies to disclose ESG information in a more standardized, transparent, and digitally accessible manner. Grewal et al. (2019) find that mandatory sustainability disclosure requirements generate significant market reactions, particularly for firms with weaker sustainability performance. Similarly, Broadstock et al. (2021) and Bae et al. (2021) demonstrate that firms with stronger ESG performance exhibited greater resilience during the COVID-19 pandemic. Otterstrom et al. (2020) further argue that recent ESG regulations in Europe have strengthened corporate transparency while promoting alignment with broader sustainability objectives.

Following the Paris Agreement, carbon neutrality and climate change have become central priorities within global sustainability policies, increasing the strategic importance of digitally disclosed ESG information for investors. Nevertheless, important challenges remain. ESG ratings differ substantially across providers due to variations in methodologies and the materiality assigned to individual indicators (Berg et al. 2022; Christensen et al. 2022). Avramov et al. (2022) show that uncertainty surrounding ESG ratings introduces additional systematic risk into sustainable investment portfolios. Krueger et al. (2020) report that institutional investors increasingly regard climate-related risks as financially material, while Serafeim and Yoon (2022) demonstrate that investors distinguish between material and immaterial ESG information when reacting to sustainability disclosures. These developments suggest that digital sustainability reporting has evolved beyond a regulatory requirement and has become a strategic instrument shaping corporate competitiveness and investor confidence.

Within this digital sustainability reporting environment, the social dimension of ESG has become an increasingly important source of information regarding employee welfare, occupational health and safety, equality, human rights, and working conditions. This study investigates the relationship between firms' ESG Social scores and employee compensation. Flammer and Luo (2017) show that employee-oriented corporate social responsibility practices enhance employee engagement and improve corporate performance. Accordingly, this study considers the social score as a proxy for employee welfare and examines the Environmental, Social, and Governance dimensions separately in order to assess their independent effects on employee compensation. Unlike previous studies that primarily evaluate ESG performance as a composite indicator (Pedersen et al. 2021; Gillan et al. 2021), this study decomposes ESG into its aggregate score and its Environmental, Social, and Governance dimensions. This approach provides a more comprehensive understanding of how each ESG pillar relates to employee compensation while offering additional evidence regarding the extent to which digitally reported social sustainability information reflects employee welfare.

Finally, the selection of large European companies is justified by their more advanced sustainability reporting practices and higher-quality ESG disclosures. Drempetic et al. (2020) demonstrate that firm size positively influences ESG performance because larger firms possess greater resources for sustainability reporting and stakeholder engagement. Given Europe's well-developed regulatory framework and its leading role in digital sustainability reporting, European firms provide an appropriate setting for examining the relationship between the social dimension of ESG and employee compensation. Furthermore, the Eurosif (2018) survey reports a substantial increase in ESG-based investment decisions across Europe, highlighting the growing importance of sustainability information within the digital investment ecosystem.

The rest of this paper is organized in the following manner. Section 2 delivers the literature review, which is the synthesis of the theoretical framework and the creation of hypotheses of the study, through the analysis of previous studies regarding sanctions, ESG performance and compensation of employees. The information and methodology are discussed in section 3; these include selecting a sample, constructing variables, cross-sectional descriptive statistics and model specifications. Section 4 gives the empirical findings and discussion, which includes the estimations that are made based on firm fixed-effects models with ESG scores. In section 5, the drivers behind the findings are discussed. Section 6 indicates the policy implications and managerial implications. Section 7 emphasizes limitations of the study and offers the future research directions. The paper is summarized in Section 8.

2. Literature review

Research on the contribution of ESG to corporate performance has gained a new dimension with the widespread adoption of digital corporate reporting practices. Today, companies communicate their sustainability performance not only through traditional corporate reports but also through digital ESG reporting systems and online sustainability disclosures. This transformation has enabled investors, regulators, and other stakeholders to evaluate ESG indicators in a more timely, transparent, and comparable manner. While traditional businesses were historically preoccupied with maximizing shareholder value, the emergence of ESG has expanded corporate performance assessment to include environmental, social, and governance dimensions. Particularly in Europe, ESG has become an integral component of corporate performance evaluation systems.

The social dimension, encompassing corporate social responsibility (CSR), labour relations, stakeholder engagement, and community development, is regarded as one of the key determinants of ESG effectiveness. CSR activities in Europe aim to ensure that corporate activities are aligned with the expectations of society. According to Carroll (1999), CSR represents a firm's responsibility to contribute to societal well-being, thereby enhancing market performance, consumer loyalty, and corporate reputation. Similarly, Porter and Kramer (2011) argue that CSR can enhance both social welfare and corporate competitiveness through the creation of shared value. Furthermore, empirical evidence indicates that European companies actively implementing CSR practices achieve higher levels of employee satisfaction, stakeholder trust, and brand equity.

The literature also highlights the importance of social and governance factors and the danger of not adhering. Siwiec (2024) also adds that, in Central and Eastern Europe, the social factors, such as the rights of labor and the engagement of the community, are a positive influence on the financial performance. Such aspects of governance as diversity in the board and managerial remuneration have a direct impact on ESG results. On the contrary, Elamer and Boulhaga (2024) concludes that the negative relationship between controversies or scandals in the ESG and financial performance is evident particularly in companies with weak governance systems. Financial structure Ktit and Abu Khalaf (2024) found that the high-scoring ESG companies have lower amount of debt and have sustainable investment policy. Da Cunha et al. (2025) allege that stable metrics and elaborate reporting standards are important in the achievement of ESG undertakings.

Social component of the ESG is related to the engagement of employees and fair labour practices. Positive labor relations comprise fair wages, diversity and inclusion (D&I) and rights of workers, which make organizations more productive, innovative, and successful over the long term (Greenwood 2013). Europe, having its rigid labor laws, cannot be an exception, and these programs oriented to the promotion of the welfare of employees have a direct effect on the sustainability of corporations. Strong labor relations help companies to achieve a higher level of profitability and better stock performance, as they have a motivated labor force and positive image (Gupta et al. 2017). Social performance is motivated by stakeholder engagement.

The stakeholder theory presumes that businesses should take into account the interest of the employees, customers, suppliers and communities rather than regarding the interest of its shareholders (Freeman 1984). Companies can build social capital, polish their brands, and increase market share using philanthropy to invest in the community and create local jobs and sustainable activities (Sullivan and Mackenzie 2017). Unilever and Danone are examples of companies that have demonstrated the positive linkage between the community participation, ESG practices, and corporate reputation. In addition, the environmental sustainability movement, labor and equality social movements, including Black Lives Matter, have put pressure on companies to change internal policies and ESG strategies (Harrison and Seidel 2020). Always the companies that are able to adapt to these social changes perform well compared to those that are not and socially responsible investing (SRI) today is on the increase in Europe (Aguilera et al. 2007; Maignan and Ferrell 2004).

The social ESG dynamics are also influenced by regulatory frameworks. Non-Financial Reporting Directive (NFRD) is a regulation by the EU that obliges the reporting of social and environmental impact, which is part of the corporate transparency and responsibility (Drempetic et al. 2020). Occurrences like these are more probable to make businesses that stick to these rules end up earning more trust among the stakeholders, as well as being better off in the long-term financial context. Diversity and inclusion are components of social aspect of ESG. Research shows that diverse leadership teams have a positive impact on decision-making, increasing innovativeness, and financial performance, and there is a 35-percent higher chance that diverse leadership teams would surpass that of the group (McKinsey 2020). The European firms, such as SAP and Siemens, have already demonstrated the beneficial outcomes of D&I, such as their increased customer interest, reduced discrimination, and satisfied staff (Momin et al. 2026).

Although these advantages are here, there are pitfalls. Most sustainability reports are not often standardized, making it difficult to compare such reports across sectors (Kotsantonis et al. 2016). There are also other complexities associated with the multinational enterprises which relate to other cultural and regulatory environments (Fischer et al. 2013). This can make tokenism out of ESGs rather than radical change due to the need to balance between profit maximization and social impact. However, more and more stakeholders are socially relevant, and social indicators are an essential element of corporate valuation in Europe (Thompson et al. 2021). Governance is a complementary aspect of the social aspect that takes care of accountability, transparency and disclosure. Good corporate governance establishes a trust relationship between the stakeholders and shareholders therefore boosting the value of the firm. Overall, European firms are becoming more and more integrated in their social responsibility in long term strategic planning and social value creation is becoming one of the fundamental aspects of competitive advantage.

Two major theories explaining the relationship between financial performance and ESG scores are available. The former is the shareholder theory which supports that the decision taken within organizations should be in the interest of the shareholders. This theory was originally expressed by Milton Friedman in Capitalism and Freedom (1962) and states that the only duty of a firm is to maximize profits to its shareholders who should be rewarded with the proportion of the risks they take in investing in the company.

This analysis addresses a big gap in the study besides it broadens the literature on the subject because it analyses the changing nature of the connection between Environmental, Social and Governance (ESG) and performance of a corporation in terms of social angle. Though the previous research has contributed greatly to the nexus of ESG and performance, very little has been done in the nexus of the specific mechanisms of how social factors affect the performance of firms, especially in the European region.

It dwells upon the history of the social responsibility and its major aspects, focusing on the social component of ESG and its impact on performance at the company. Historically, companies have been preoccupied with maximizing the shareholder value but with time the ESG standards have replaced it as a major measure of the performance of companies especially in Europe. The social dimension, consisting of such elements as corporate social responsibility (CSR), labor relations, interaction with stakeholders and community development, plays a pivotal role in the effectiveness of ESG.

3. Data and methodology

This study examines the social dimension of ESG, specifically whether a higher social score reflects the appropriate treatment of employees. This study focuses on European companies over a ten-year period (2011-2020), capturing both post-financial crisis recovery and the onset of the COVID-19 pandemic. Previous studies have highlighted that following the financial crisis, ESG performance has gained importance in firm evaluation due to its influence on market value. The database chosen is Refinitv Eikon from Thomson Reuters, which provides ESG data for over 9,000 companies worldwide. The data cover 450+ ESG data points dating back to 2002 and are measured in a transparent and objective manner. Such information is collected from annual financial statements, companies' official websites, CSR reports, news updates, and other relevant sources. The scores are based on ten main themes shown in Figure 1. The scoring methodology includes several principles. First, the metric's magnitude was mapped in line with the industry on a scale of 1 to 10. If companies fail to disclose material data, this will have a negative effect on their scores. Moreover, this methodology ensures that the market cap bias is accounted for. Therefore, any controversial scores are adjusted according to firm size. To facilitate comparison, industry and country benchmarks are established at the date scoring level. Finally, to avoid hidden calculations, percentile rank scoring was used. The ESG scores are recalculated every week as the data are continually updated.

$$\text{No. of firms with a worse value} + \text{No. of firms with the same value included in the}$$
$$\text{current on Score} = \frac{2}{\text{No. of firms with a value}} \tag{1}$$

Equation (1) shows how the ESG scores are calculated on Thomson Reuters. Each score for each theme can take a value of zero to hundred.

Figure 1. ESG score composition

3.1. Sample selection

The dataset spans 10 years and includes companies listed in the S&P 350 Index, comprising 350 blue-chip firms across 16 developed European markets. The index focuses on the largest and most liquid equities and is weighted by float-adjusted market capitalization, including both common and preferred shares, to maintain balanced country and sector representation. All relevant data were obtained from Thomson Reuters using Refinitiv Eikon ESG company scores. The S&P 350 sample covers 11 sectors: communication services (n = 22), consumer discretionary (n = 38), consumer staples (n = 28), energy (n = 10), financials (n = 60), healthcare (n = 23), industrials (n = 66), information technology (n = 16), materials (n = 32), real estate (n = 7), and utilities (n = 21). To address the main research question, the analysis was further segmented to explore different perspectives on the social dimension of ESG performance.

The Index chosen is composed of 350 leading companies, based on size and liquidity. The choice is based on the 11 Global Industry Classification Standard (GICS) and 16 major developed European markets.

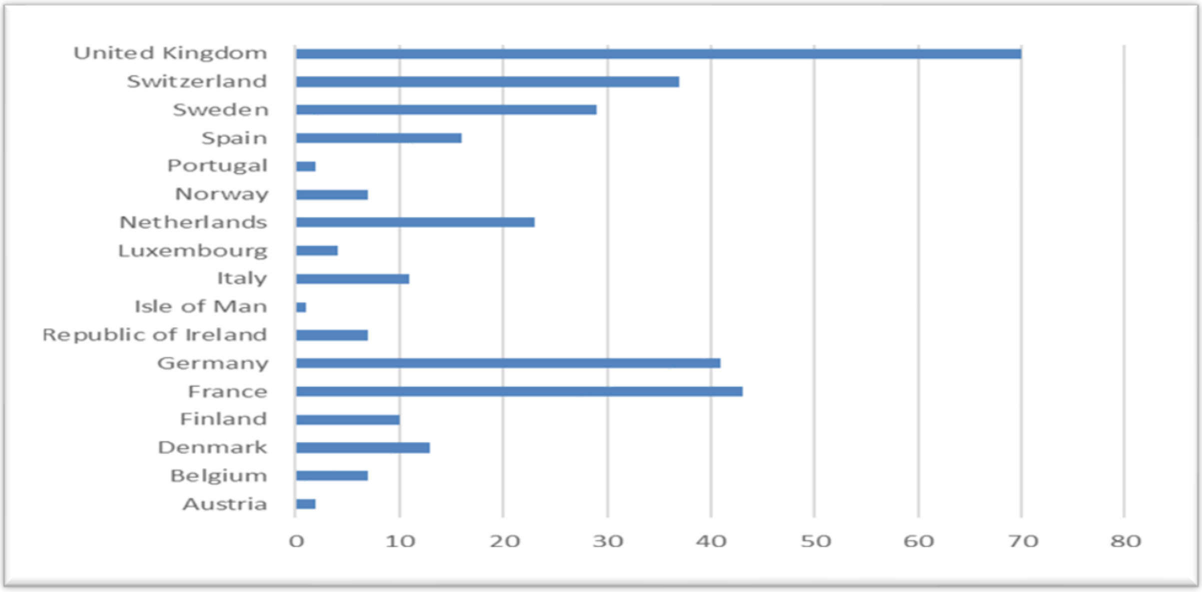

Figure 2. List of countries

The S&P 350 Index used in this study has the highest exposure in the United Kingdom, France, and Germany, with minor representation from countries such as the Isle of Man, Portugal, and Austria. It includes three sub-indices: S&P Euro-Equities, which covers developed Eurozone countries (Austria, Belgium, Finland, France, Germany, Ireland, Italy, Luxembourg, Netherlands, Portugal, and Spain); S&P Euro Plus, which adds other developed European countries (Denmark, Norway, Sweden, and Switzerland); and S&P United Kingdom, which focuses solely on UK equities (S&P Dow Jones Indices 2020). Figure 2 presents the list of countries included in the analysis and their respective shares.

Data were sourced from Refinitiv Eikon via Thomson Reuters because of its comprehensive and transparent ESG methodology, as emphasized by Siew (2015), who highlighted the importance of ESG disclosure. The dataset is panel in nature, allowing for the control of unobservable firm-specific heterogeneity across time and companies (Stock and Watson 2015; Brooks 2014). Panel data also increase the efficiency of estimation because of the larger number of observations.

The panel in this study is unbalanced, with some firms missing data for certain years. This was deemed acceptable because imputing missing values could reduce validity. The unbalanced structure allows firms with incomplete records to remain in the sample without introducing any bias. A large firm size mitigates concerns over wage variations due to seasonality or turnover. A firm-fixed effects model was employed to control for omitted variables that differ across firms but are time-invariant. This model includes a firm-specific intercept (αi) to capture individual heterogeneity and remove any time-invariant effects, thereby reducing the omitted-variable bias (Stock and Watson 2015). Given the 10-year period for each firm, this approach effectively accounts for constant firm-level characteristics while isolating the impact of ESG and social scores on wages. The regressions are:

$$Y_{it} = \alpha_i + \beta_1 ESG_{it-1} + \beta_2 R\&D_{it-1} + \beta_3 SIZE_{it-1} + \beta_4 CAPEX_{it-1} + U_{it-1} \quad (2)$$

$$Y_{it} = \alpha_i + \beta_1 Social\ Score_{it-1} + \beta_2 R\&D_{it-1} + \beta_3 SIZE_{it-1} + \beta_4 CAPEX_{it-1} + U_{it-1} \quad (3)$$

Equation (2) specifies the fixed-effects regression model in which the ESG score is employed as the dependent variable. Similarly, Equation (3) specifies the fixed-effects regression model with the social score as the dependent variable.

All relevant data used in this study were collected from Thomson Reuters; therefore, the ESG scores used are all from Refinitiv ESG scores. All data in this study were converted into USD to have the same base currency across all variables and to conduct the regression. The choice of variables for the impact of ESG differs among previous studies. In this study, the dependent variable for the regression is the average wage level. This variable will be calculated from data found, being the cost of labor per number of employees. This variable was chosen to represent employees' satisfaction at work. This is because the aim of this study is to test whether a high social score signifies a rise in employee satisfaction and working conditions; hence, a better wage.

$$Wages = \frac{Labour \,\&\, Related\ Expenses}{Number\ of\ Employee} \tag{4}$$

Equation (4) presents the specification of the model with the dependent variable. The ESG score represents a composite measure of corporate social responsibility across multiple dimensions, including working conditions, equality, and health and safety standards, and ranges from 0 to 100. It aggregates firm-level performance relative to peers, using comparable data points. Firms lacking complete ESG data over the 10-year study period were excluded to ensure consistency, resulting in a final sample of 323 firms. While this screening enhances data reliability, it may introduce selection bias, which is discussed further in the limitations section.

Table 1. Correlation matrix

	Wages	Total Assets	CAPEX	ESG-Score	S-Score	E-Score	G-Score
Wages	1						
Total Assets	0.176475	1					
CAPEX	-0.0802	0.574117	1				
ESG-Score	-0.0399	0.397655	0.501411	1			
S-Score	-0.0502	0.371536	0.49053	0.794653	1		
E-Score	-0.073	0.276843	0.44055	0.873144	0.655605	1	
G-Score	0.039574	0.342097	0.283672	0.687079	0.312718	0.361368	1

Given the large magnitudes of the variables, logarithmic transformations were applied, and all control variables were lagged by one period. A correlation matrix was generated in E-Views to examine the relationships among the variables. The results of the correlation matrix are presented in Table 1. The results reveal strong correlations among the ESG pillars, with the highest correlation observed between the overall ESG score and the Environmental Score (0.87), followed by the social score (0.79). This suggests that the Governance Score contributes relatively less to the composite ESG measure.

Regarding wages, firm size proxied by total assets shows the strongest positive correlation, indicating that larger firms tend to pay higher wages than smaller firms. In contrast, both the ESG and Social scores display negative correlations with wages, contrary to prior expectations. Total assets, capital expenditure, and ESG-related scores were positively correlated, implying that larger firms placed greater emphasis on ESG activities, particularly environmental sustainability. It is important to note that correlation analysis is primarily used to detect potential multicollinearity rather than causal relationships. Excluding the correlations among ESG components, the highest observed correlation is between total assets and capital expenditure (0.57), which does not raise multicollinearity concerns (Brooks 2014). Table 2 shows the average change in wages and the number of wage increases between 2011 and 2020.

Table 2. Description of wages

Year	Average of Wages	Count of Wages
2011	220,752	176
2012	88,327	212
2013	93,555	236
2014	96,303	244
2015	95,650	260
2016	90,521	274
2017	94,357	272
2018	93,500	277
2019	89,244	277
2020	299,719	232

The maximum number of observations was 323. The observations for the independent variables vary from 176 to 323 from 2011 to 2020. Another variable that was excluded from the study is the Research & Development variable, which was omitted due to the lack of observations. The issue for this omitted variable is minimal; hence, it was decided to exclude it from the regression. Despite this, it is still a cause of concern with respect to the validity of the results. The number of observations for the dependent variable varies from 176 to 277, where the lowest year of observations was in 2011. These results are visually presented in Figure 3.

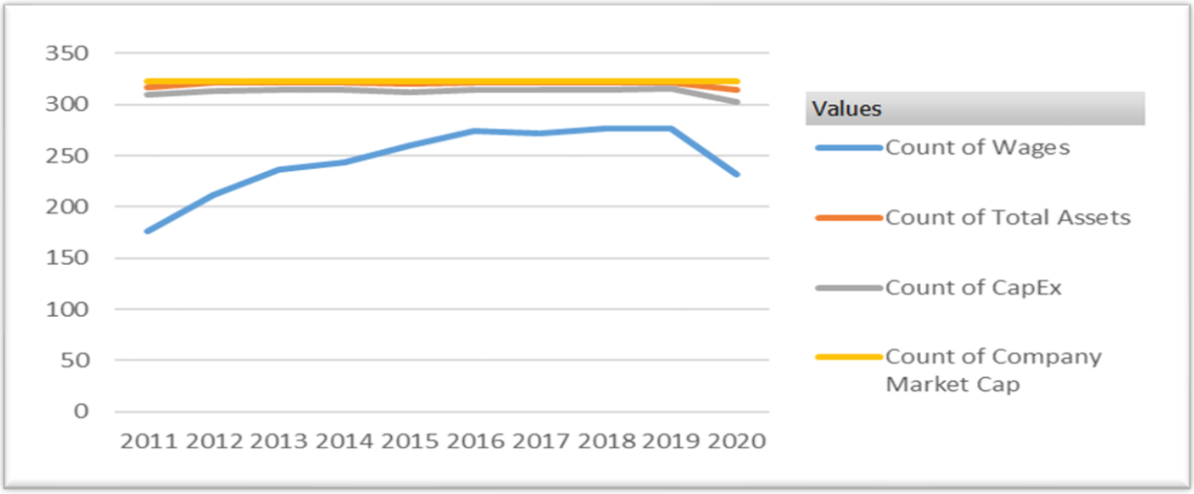

Figure 3. Number of observations

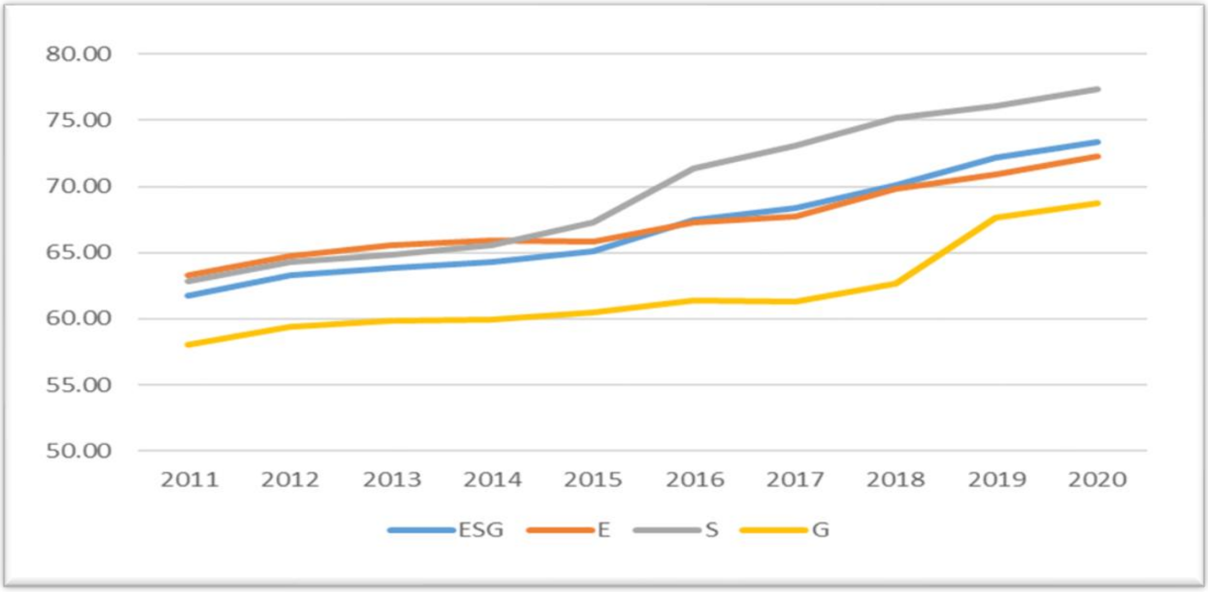

Figure 4. Average of ESG scores

Figure 4 shows the average ESG scores, and all 11 sectors showed an improvement in their average ESG score during the study period. This is in line with the previous literature, as the focus on ESG has increased over the years. All scores increased by approximately 10 points from 2011 to 2020. The Social score shows a higher increase, which is also in line with the belief of this study, as it has gained momentum in recent years.

The Figure 5 compares the mean and median average wages across different industries. This will be useful for evaluating the study. By making the data conditional on the sector, wages in the same sector should be similar across peers, making it easier to detect any possible outliers. The orange bars represent the median, and a possible explanation for the deviation from the mean could be the variation across time. In certain sectors, the mean and median are almost equal, indicating that the distribution of wages is symmetric based on the respective industry. Meanwhile, in the financial and real estate sectors, the mean is higher than the median, which is usually the case for a positively skewed distribution.

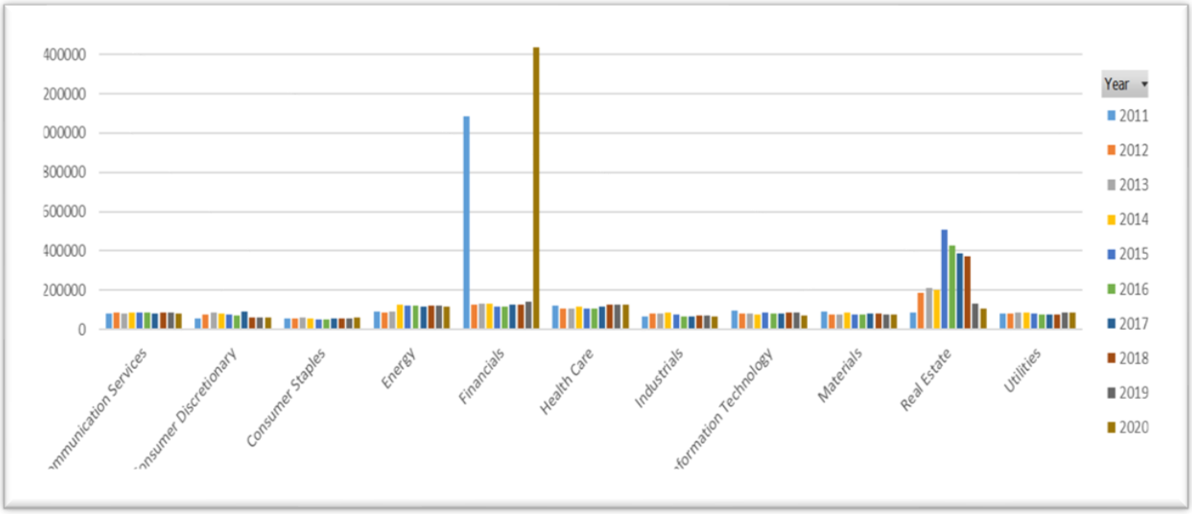

Figure 5. Average of wages per industry

There is a conflict of belief when it comes to outliers, which might distort the regression, as these do not fit the pattern of the data. Brooks states that if these observations are removed, this would mean that the results are fabricated. Therefore, it was decided that if there were any outliers in this study, they would not be removed, given that they were not a manual mistake.

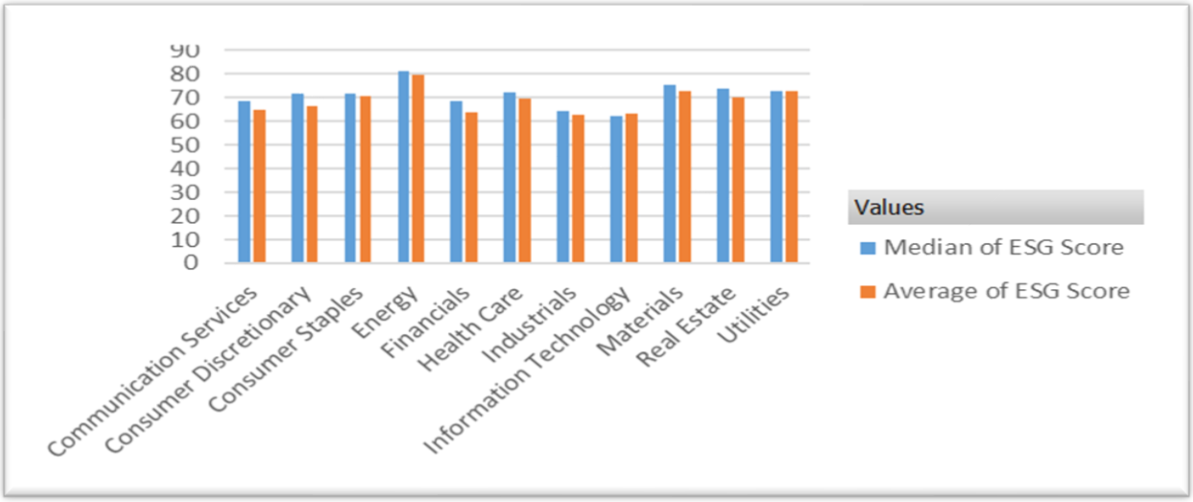

Figure 6. Average values of ESG score per industry

Figure 6 presents the average ESG scores across industries. The same method can be used to detect potential outliers in ESG scores. There does not seem to be any significant difference between the mean and median, based on the respective sectors. The only difference is for consumer discretionary, which has a five-point difference, with the median higher than the mean. This implies a negatively skewed distribution of the data. When taking a deeper look at the distribution of the consumer discretionary industry with respect to the ESG score, there do not seem to be any outliers. Data in the intervals range from 2.81 to 94.50 and are not due to a data-entry mistake.

The ESG scores seem to have some variation between the mean and median values, with a high standard deviation. These variables had no missing data, allowing for 3,229 observations. There was a significant difference between the maximum and minimum values, indicating distant outliers, while the mean and median values were satisfactory. The lowest score is recorded by the governance sector, with a mean of 61.95, indicating a tougher grading score or companies showing less interest in improvement. The Environmental Score has a slightly higher mean, which indicates that the firms chosen in the sample tend to prioritize environmental aspects in their sustainability engagements. This is in line with expectations, especially since it is followed by the Social score. The social aspect of firms is increasing in importance, showing that companies are becoming more aware that workers need to be treated in the best possible way for the success of the company as a whole. The main idea is that firms will enjoy improved scores while employees will be more satisfied with higher wages.

Table 3. Descriptive statistics

	Wages	Total Assets	CAPEX	ESG-Score	S-Score	E-Score	G-Score
Mean	11.234	24.08797	20.15222	66.96996	67.33485	69.7678	61.94583
Median	11.235	23.91138	20.17709	70.02698	73.08704	74.53288	65.53943
Maximum	17.7123	28.66115	24.41576	95.0166	99.25239	98.64374	97.93489
Minimum	5.4349	19.42281	11.79587	2.813508	0	2.169435	3.459516
Std. Dev.	0.6391	1.72895	1.678846	17.3388	22.6425	20.13778	21.15874
Skewness	-0.2911	0.459531	-0.27753	-1.02954	-0.98908	-0.98628	-0.55259
Kurtosis	20.3282	2.766882	3.397856	3.965622	3.386366	3.494426	2.487348
Observations	2460	3202	3128	3229	3229	3229	3229

Table 3 reports the descriptive statistics for all variables included in the analysis. When looking at wages, there is quite a gap between the median and maximum, which could be due to the size of the firm or the employee's level of work. Some companies may employ professionals, while others may need laborers for day-to-day operations. The total assets variable accounts for company size. The maximum observations indicate that firms have a logarithmic value of $28.7 in total assets while the minimum is at $19.4. However, the mean is at $24.1, showing that the average is higher than the median. The maximum and minimum observations of the capital expenditure variable show how many dollars the firms spend on capital. The mean seems to be on the higher side, closer to the maximum observation at $20.15.

4. Analysis and results

Model-building tests were used for the ideal model choice. Moreover, the results obtained using the models are explained. As previously mentioned, three models were chosen, and for each model, two tests were run using the ESG score and Social score, respectively. With the use of panel data, heterogeneity is considered, while multicollinearity is avoided, which tends to be found in time series data. For each model, two regressions were run: the first using the overall ESG score and the second using the Social score as an explanatory variable. Equation (5) presents the time fixed-effects regression model using the ESG score as the dependent variable.

$$Y_{it} = \alpha_i + \beta_1 ESG_{it-1} + u_{it-1} \quad (5)$$

Table 4. Time-fixed effect using ESG score

Wages	Coefficient	Standard Error	P-Value
ESG	-0.003183	0.000800	0.0001
Constant	11.44612	0.054978	0.0000
Adjusted R-Squared	0.005100		
Total panel observations	2,284		

The analysis results for this model are presented in Table 4. The relationship is negative, meaning that firms with higher ESG scores do not pay higher average wages. In fact, they pay lower wages, so there seems to be a disconnection between what they claim to be doing and the way they treat their workers. From a statistical perspective, in the fixed effects model, the negative coefficient of the ESG score versus wages means that there is a negative relationship between a higher ESG score and wages in the following period. This means that in the following year, wages will be lower, and hence employee satisfaction will decline. This favors the shareholder theory. However, the adjusted R-squared is very low, which means that the ESG score alone does not explain much of the variation in wages. Despite the p-value being statistically significant, the indicates that the independent variable, the ESG score, does not account for much of the mean of the dependent variable, the level of wages.

The same regression was run, but this time including the control variables, to get a better understanding of what impacts the level of wages. Equation (6) presents the time fixed-effects regression model with the ESG score as the dependent variable and the inclusion of control variables.

$$\mathrm{Y_{it}} = \alpha_\mathrm{i} + \beta_1\mathrm{ESG_{it-1}} + \beta_2 Size_{it-1} + \beta_3 CAPEX_{it-1} + \mathrm{u_{it-1}} \quad (6)$$

Table 5. Time-fixed effect using ESG score and control variables

Wages	Coefficient	Standard Error	P-Value
ESG	-0.003537	0.000953	0.0002
Size (Total Assets)	0.119751	0.008975	0.0000
CAPEX	-0.078699	0.010314	0.0000
Constant	10.17012	0.193246	0.0000
Adjusted R-Squared	0.079673		
Total panel observations	2,260		

The analysis results for this model are presented in Table 5. When the control variables, size and capital expenditure, were included in the regression, the coefficient of the ESG score remained negative, implying that employees tend to be less satisfied when firms post higher ESG scores. On the other hand, the size of the firms seems to have a positive impact on wages, while capital expenditure is observed to have a negative relationship with respect to wages. These results are in line with expectations, since one would not expect an increase in wages if capital expenditure is increasing. On the other hand, the larger the firm, the higher the likelihood of receiving a better salary.

This time, the industry dummy variables are included to test for the industry-fixed effect. Each industry was assigned a number to facilitate the generation of statistical tests. The aim of including these variables is to determine how each industry impacts the level of average wages. The same regression was run, considering the industry effect. To generate the dummy variables (D) in e-views, each industry was assigned a number. Equation (7) presents the time fixed-effects regression model with ESG score and industry dummy variables.

$$\mathrm{Y_{it}} = \alpha_\mathrm{i} + \beta_1\mathrm{ESG_{it-1}} + \gamma_2 D_{i,1} + \ldots + \gamma_{14} D_{i,10} + \mathrm{u_{it-1}} \quad (7)$$

The analysis results for this model are presented in Table 6. In this regression, only 10 dummy variables were included; therefore, the utility dummy variable was used as the reference variable for encoding the regression. When including the industry dummy variables in the regression, the ESG score still turned out to be negative and statistically significant when using the time-fixed effect. However, the adjusted R-squared is still low, explaining only approximately 23% of the observed variance. The different industries were controlled for in the regression, given that each sector carries a different risk level, which could lead to potential outperformance versus other sectors in wages. The consumer discretionary, consumer staples, and industrial sectors all have statistically significant negative coefficients. This shows that these sectors can have a negative relationship with wage levels. In contrast, the energy, financial, healthcare, and real estate industries indicate a positive relationship with wages, meaning that income in these sectors is higher. Meanwhile, the communication services, information technology, and materials sectors show no statistical significance in relation to the level of wages.

Therefore, whether these are present or not in the regression appears to have no correlation with the wages.

Table 6. Time-fixed effect using ESG score and industry dummy variables

Wages	Coefficient	Standard Error	P-value
ESG	-0.004677	0.000733	0.0000
Constant	11.59662	0.067223	0.0000
Υ_5 = Communication Services	-0.056727	0.059962	0.3442
Υ_6 = Consumer Discretionary	-0.416529	0.052828	0.0000
Υ_7 = Consumer Staples	-0.467372	0.055746	0.0000
Υ_8 = Energy	0.333992	0.077255	0.0000
Υ_9 = Financials	0.336355	0.050179	0.0000
Υ_{10} = Healthcare	0.291090	0.059279	0.0000
Υ_{11} = Industrials	-0.224287	0.048643	0.0000
Υ_{12} = Information Technology	-0.017944	0.074782	0.8104
Υ_{13} = Materials	-0.050775	0.054999	0.3560
Υ_{14} = Real Estate	0.636030	0.083203	0.0000
Adjusted R-Squared	0.229392		
Total panel observations	2,284		

The same regression was tested for, this time including the control variables, using the time-fixed effect. The aim here is to test whether these might have an impact on the results achieved so far. Equation (8) presents the time fixed-effects regression model with ESG score, control variables, and industry dummy variables.

$$\mathrm{Y_{it}} = \alpha_i + \beta_1 \mathrm{ESG_{it-1}} + \beta_2 Size_{it-1} + \beta_3 CAPEX_{it-1} + \gamma_2 D_{i,1} + \ldots + \gamma_{14} D_{i,10} + \mathrm{u_{it-1}} \quad (8)$$

Table 7. Time-fixed effect using ESG score, control variables and industry dummy variables

Wages	Coefficient	Standard Error	P-value
ESG	-0.003415	0.000899	0.0002
Size (Total Assets)	0.079584	0.016406	0.0000
Capex	-0.072645	0.013900	0.0000
Constant	11.11448	0.234862	0.0000
Υ_5 = Communication Services	-0.042229	0.058484	0.4703
Υ_6 = Consumer Discretionary	-0.485158	0.053143	0.0000
Υ_7 = Consumer Staples	-0.485674	0.055033	0.0000
Υ_8 = Energy	0.351895	0.075490	0.0000
Υ_9 = Financials	0.050245	0.073406	0.4937
Υ_{10} = Healthcare	0.282497	0.059021	0.0000
Υ_{11} = Industrials	-0.235902	0.048694	0.0000
Υ_{12} = Information Technology	-0.046031	0.074725	0.5380
Υ_{13} = Materials	-0.043859	0.054996	0.4253
Υ_{14} = Real Estate	0.617431	0.081848	0.0000
Adjusted R-Squared	0.249559		
Total panel observations	2,260		

The analysis results for this model are presented in Table 7. Similarly, the coefficient of ESG remains negative when explanatory variables are included and is statistically significant. As in the previous case, size has a positive impact on wages, whereas higher capital expenditure lowers the level of wages. This time, the adjusted R-squared is higher, suggesting that approximately 62% is explained in this regression.

Moving on to the dummy variables, the results were similar, except for the financial sector. When including the control variables, the coefficient, despite still being positive, was not statistically significant since the P-value stood at 0.4703, hence greater than 0.05. The real estate sector seems to have the highest positive impact on wages. The variable is also statistically significant, meaning that the wages of employees in this sector are more favorable. Similarly, the energy and healthcare sectors can also positively affect our dependent variable, that is, the level of wages. On the other hand, the consumer discretionary, consumer staples, and industrials industries have a negative coefficient, with a statistically significant P-value lower than the 0.05 level. This means that employees in these industries tend to have a negative relationship with wages through lower pay.

4.1. Using firm-fixed effects with ESG score

In the following part, instead of using the time-fixed effect, the firm-Fixed Effect was used. With firm fixed effects, things change drastically. There is something at the firm level, which is unobserved heterogeneity, captured by the firm-fixed effect. Therefore, the firm-fixed effects capture everything that can be controlled for things that are observed and unobserved. Therefore, at the firm level, could be culture or the business model. Since industry is time invariant within companies, this model includes the industry fixed effect, making it more robust. This is because more unobservable factors are controlled for, including different industries.

When using the firm-fixed effect, the ESG score's coefficient is positive, meaning that a high ESG rating translates into higher wages when looking at differences that cannot be measured directly. Such differences are captured by the σ. Equation (9) presents the firm fixed-effects regression model with ESG score as the dependent variable.

$$Y_{it} = \alpha_i + \beta_1 ESG_{it-1} + \sigma_i + u_{it-1} \tag{9}$$

The analysis results for this model are presented in Table 8. The firm-fixed effects regression utilizing the ESG score yielded a positive coefficient, suggesting that firms with superior ESG performance are inclined to provide more favorable treatment to their employees. Although the p-value slightly exceeded 0.05, it remained close to the statistical significance. The adjusted R-squared value of 74% indicates a robust explanatory power, implying that firm-level characteristics significantly influence this relationship.

Table 8. Firm-fixed effect using ESG score

Wages	Coefficient	Standard Error	P-Value
ESG	0.002056	0.001052	0.0507
Constant	11.09646	0.070518	0.0000
Adjusted R-Squared	0.740225		
Total panel observations	2,284		

The firm-fixed effects model was used again to run the same regression, including the control variables. This way, the endogeneity problem can be reduced while also capturing time-variant unobserved firm characteristics. Equation (10) presents the firm fixed-effects regression model with ESG score and control variables.

$$Y_{it} = \alpha_i + \beta_1 ESG_{it-1} + \beta_2 Size_{it-1} + \beta_3 CAPEX_{it-1} + \sigma_i + u_{it-1} \tag{10}$$

The analysis results for this model are presented in Table 9. When using the firm-fixed effect with the independent variables, the coefficient of ESG was positive and statistically significant. This means that at the firm level, firms that claim to have a high ESG tend to pay their employees higher wages. Moreover, the adjusted R-squared is 0.78, so the proposed determinants explain around 78% of the variance in wages. Both size and capital expenditure are statistically insignificant because the p-value is greater than 0.05. However, both have a negative effect on wages. The unobserved heterogeneous factors indicated that the impact of higher ESG scores was positive. Each individual firm compares what is happening within the same firm. Therefore, controlling for everything else, when a firm changes its ESG score to a better one, this will positively impact the level of wages of the same firm.

Table 9. Firm-fixed effect using ESG score and control variables

Wages	Coefficient	Standard Error	P-Value
ESG	0.002143	0.001092	0.0498
Size (Total Assets)	-0.028153	0.036534	0.4410
CAPEX	-0.018626	0.020488	0.3634
Constant	12.13412	0.792283	0.0000
Adjusted R-Squared	0.775010		
Total panel observations	2,260		

The firm-fixed effect is also used to check the growth rate and average values of the ESG score and control variables. According to Table 10, the growth rate and average value of the variables, the ESG score, has a negative coefficient. This implies that, on average, firms that record a higher ESG score tend to pay their workers less.

Table 10. Firm-fixed effect with growth rate of wages and average of ESG score and control variables

Wages	Coefficient	Standard Error	P-Value
ESG	-1672.185	6528.751	0.7980
Size (Total Assets)	-109347.0	60207.69	0.0703
CAPEX	46445.22	62681.70	0.4593
Constant	1618614.	1334324.	0.2260
Adjusted R-Squared	0.010849		
Total panel observations	316		

In the regression that included the dummy variables, all firms with a negative coefficient were put together as a grouped (Table 11). The same was done for the industries that had a positive coefficient. In this case, the following industries were included because they had a negative coefficient: communication services, consumer discretionary, consumer staples, industrials, information technology, and materials.

According to Table 12, the results show that when focusing on these industries, the coefficient of the ESG score is still negative and statistically significant. In the time-fixed effect model, ESG has a negative relationship with the level of average wages. This is because there are unobserved factors that are not being tested in such a mode.

Table 11. Time-fixed effect using ESG score and negative dummy variables

Wages	Coefficient	Standard Error	P-Value
ESG	-0.003332	0.001058	0.0017
Size (Total Assets)	0.100757	0.022348	0.0000
CAPEX	-0.066341	0.017644	0.0002
Constant	10.22849	0.309021	0.0000
Adjusted R-Squared	0.023399		
Total panel observations	1,434		

The negative coefficient for the ESG score. However, the coefficient for the ESG score of the positive dummy variables is statistically insignificant. This means that when using the time-fixed effect, the ESG score seems to always have a negative relationship with wages.

Table 12. Time-fixed effect using ESG score and positive dummy variables

Wages	Coefficient	Standard Error	P-Value
ESG	-0.002269	0.001980	0.2523
Size (Total Assets)	-0.012080	0.012981	0.3524
CAPEX	-0.032140	0.018301	0.0795
Constant	12.73264	0.350237	0.0000
Adjusted R-Squared	0.018768		
Total panel observations	650		

The same regressions were run, this time using the firm-fixed effect, to test for any potential unobserved heterogeneous factors (Table 13). Meanwhile, for the positive dummy variables, the industries were energy, financial, healthcare, and real estate.

Table 13. Firm-fixed effect using ESG score and negative dummy variables

Wages	Coefficient	Standard Error	P-Value
ESG	0.003421	0.001521	0.0246
Size (Total Assets)	-0.077135	0.051201	0.1322
CAPEX	-0.025388	0.033136	0.4437
Constant	13.12924	1.046135	0.0000
Adjusted R-Squared	0.628510		
Total panel observations	1,434		

With firm-fixed effects, the ESG score turned out to be positive for industries with a negative coefficient (Table 13). Therefore, there is a positive effect, which seems to be stronger when compared to the same regression run, including industries that had a positive coefficient.

Table 14. Firm-fixed effect using ESG score and positive dummy variables

Wages	Coefficient	Standard Error	P-Value
ESG	0.000437	0.001620	0.7872
Size (Total Assets)	0.070838	0.056230	0.2083
CAPEX	-0.004180	0.026508	0.8747
Constant	9.888356	1.348156	0.0000
Adjusted R-Squared	0.795281		
Total panel observations	650		

The coefficient of the ESG score, despite being positive, is not statistically significant (Table 14). When using the firm-fixed effect, the level of wages is analyzed with an increase in ESG, controlling everything at the firm level. Therefore, one is looking inside the firm and comparing what is happening within the same firm. Therefore, when controlling for everything else, when a firm changes its ESG score, there is subsequently an increase in the average wage within the firm.

The first regression was run using the Social score alone, using the time-fixed effect, to test the impact of the Social score alone on the level of wages. It is important to note that we control for any macroeconomic shocks to obtain unbiased results. However, we only controlled for any observed or unobserved systematic differences between the observed time frames. Equation (11) presents the time fixed-effects regression model with Social score as the dependent variable.

$$Y_{it} = \alpha_i + \beta_1 \textit{Social score}_{it-1} + u_{it-1} \tag{11}$$

The analysis results for this model are presented in Table 15. The time-fixed effects analysis identified a statistically significant negative coefficient for the Social score, indicating that firms with higher declared social responsibility tend to offer lower employee wages. The discrepancy between corporate claims of social commitment and internal labor practices. Statistically, the fixed effects model corroborates a negative association between elevated Social scores and subsequent wage levels, potentially diminishing employee satisfaction. However, the low adjusted R-squared value (approximately 1%) suggests that the Social score alone inadequately explains wage variations, highlighting the need for additional variables.

Table 15. Time-fixed effect using social score

Wages	Coefficient	Standard Error	P-Value
Social score	-0.003608	0.000677	0.0000
Constant	11.48416	0.048749	0.0000
Adjusted R-Squared	0.014441		
Total panel observations	2,284		

To increase the R-squared value, control variables were included to increase the explanation of movement in wages. Equation (12) presents the time fixed-effects regression model with Social score and control variables.

$$\mathrm{Y_{it}} = \alpha_i + \beta_1 \mathrm{Social\ score_{it-1}} + \beta_2 Size_{it-1} + \beta_3 CAPEX_{it-1} + \mathrm{u_{it-1}} \tag{12}$$

The analysis results for this model are presented in Table 16. When the control variables are included, the coefficient of the Social score remains negative and statistically significant. This time, the adjusted R-squared is slightly higher at 8%, but is still considered low. The size variable has a positive impact on wages, as with every one-unit increase, wages increase by 0.115407 units. Therefore, total assets determine wages effectively. On the other hand, capital expenditure has a negative effect on wages, with a statistically significant coefficient of -0.078723. This is in line with our expectations, as higher expenses would make it less likely to increase wages.

Table 16. Time-fixed effect using social score and control variables

Wages	Coefficient	Standard Error	P-Value
Social score	-0.002918	0.000756	0.0001
Size (Total Assets)	0.115407	0.008843	0.0000
CAPEX	-0.078723	0.010246	0.0000
Constant	10.24146	0.188035	0.0000
Adjusted R-Squared	0.075625		
Total panel observations	2,260		

When including the dummy variables in the regression, a more in-depth explanation is provided as to what really impacts the level of wages. In this way, industry-fixed effects are tested. Equation (13) presents the time fixed-effects regression model with Social score and industry dummy variables.

$$\mathrm{Y_{it}} = \alpha_i + \beta_1 \mathrm{Social\ score_{it-1}} + \gamma_2 D_{i,1} + \ldots + \gamma_{14} D_{i,10} + \mathrm{u_{it-1}} \tag{13}$$

The analysis results for this model are presented in Table 17. After including the dummy variables, the Social score remained negative; however, the adjusted R-squared, despite being higher, is still considered low at 23%. Consumer discretionary, consumer staples, and industrials have a negative statistically significant coefficient, meaning that they have a negative relationship with wages. Conversely, the energy, financial, healthcare, and real estate sectors have positive coefficients. The results are in line with that of hypothesis one, meaning that when using the time-fixed effect, the regressions suggest that a higher score signifies a negative relationship with the level of wages.

Table 17. Time-fixed effect using ESG score and industry dummy variables

Wages	Coefficient	Standard Error	P-value
Social score	-0.003737	0.000617	0.0000
Constant	11.54444	0.062772	0.0000
Υ_5 = Communication Services	-0.053279	0.059990	0.3746
Υ_6 = Consumer Discretionary	-0.413403	0.052852	0.0000
Υ_7 = Consumer Staples	-0.460341	0.055772	0.0000
Υ_8 = Energy	0.320245	0.077240	0.0000
Υ_9 = Financials	0.322277	0.050515	0.0000
Υ_{10} = Healthcare	0.297139	0.059284	0.0000
Υ_{11} = Industrials	-0.216219	0.048540	0.0000
Υ_{12} = Information Technology	-0.008206	0.074768	0.9126
Υ_{13} = Materials	-0.067096	0.055091	0.2234
Υ_{14} = Real Estate	0.633576	0.083290	0.0000
Adjusted R-Squared	0.234473		
Total panel observations	2,284		

Equation (14) extends the time fixed-effects regression model by incorporating Social score, control variables, and industry dummy variables.

$$\mathrm{Y_{it}} = \alpha_i + \beta_1 \text{Social score}_{it-1} + \beta_2 Size_{it-1} + \beta_3 CAPEX_{it-1} + \gamma_2 D_{i,1} + \ldots + \gamma_{14} D_{i,10} + \mathrm{u}_{it-1} \tag{14}$$

The analysis results for this model are presented in Table 18. With the inclusion of control variables, the Social score remains negative and statistically significant in the time-fixed effects model. Firm size is positively associated with wages, whereas capital expenditure has a negative effect. The results show positive wage effects in real estate, energy, and healthcare, whereas consumer discretionary, consumer staples, and industrials exhibit significantly lower wages.

Table 18. Time-fixed effect using social score, control variables and industry dummy variables

Wages	Coefficient	Standard Error	P-value
Social score	-0.002372	0.000705	0.0008
Size (Total Assets)	0.073246	0.016130	0.0000
Capex	-0.073495	0.013911	0.0000
Constant	11.22292	0.228476	0.0000
Υ_5 = Communication Services	-0.041221	0.058533	0.4814
Υ_6 = Consumer Discretionary	-0.490201	0.053135	0.0000
Υ_7 = Consumer Staples	-0.485995	0.055093	0.0000
Υ_8 = Energy	0.344943	0.075545	0.0000
Υ_9 = Financials	0.054360	0.073462	0.4594
Υ_{10} = Healthcare	0.279251	0.059032	0.0000
Υ_{11} = Industrials	-0.235779	0.048729	0.0000
Υ_{12} = Information Technology	-0.048553	0.074767	0.5162
Υ_{13} = Materials	-0.062500	0.054600	0.2525
Υ_{14} = Real Estate	0.609368	0.081822	0.0000
Adjusted R-Squared	2,260		
Total panel observations	0.248525		

In this section, to test for unobserved heterogeneity, the firm-fixed effect was used. The analysis results for this model are presented in Table 19. This is because this method captures everything that can be controlled, both observed and unobserved factors for each individual firm in the panel data. As in hypothesis1, when using the firm-fixed effect, the Social score has a positive effect on the level of wages. In addition, the adjusted R-squared is at 0.74, which shows that this regression explains 74% of the variance in wages.

Table 19. Firm-fixed effect using social score

Wages	Coefficient	Standard Error	P-Value
Social score	0.002448	0.000764	0.0014
Constant	11.06377	0.053462	0.0000
Adjusted R-Squared	0.741064		
Total panel observations	2,284		

The firm-fixed effects model was re-estimated using wage-related control variables to account for unobserved firm-level heterogeneity. The analysis results for this model are presented in Table 20. Under this specification, the social score exhibits a positive and statistically significant coefficient, while the adjusted R-squared indicates that approximately 78 per cent of the variation in wages is explained. At the firm level, higher social scores are associated with greater employee satisfaction through higher wages. Although firm size and capital expenditure carry negative coefficients, both are statistically insignificant. The initial hypothesis was that once unobserved heterogeneous factors are controlled for, higher social scores have a positive effect on wage levels, consistent with the expectation that improved social performance reflects better working conditions.

Table 20. Firm-fixed effect using social score and control variables

Wages	Coefficient	Standard Error	P-Value
Social score	0.002726	0.000785	0.0005
Size (Total Assets)	-0.022641	0.020494	0.2694
CAPEX	-0.036216	0.036169	0.3168
Constant	12.36257	0.790705	0.0000
Adjusted R-Squared	0.741504		
Total panel observations	2,260		

The firm-fixed effects model was also estimated using both the growth rates and average values of the social score and control variables, with all industries pooled to obtain an overall effect. The analysis results for this model are presented in Table 21. In this specification, the social score displays a positive coefficient, indicating that, on average, firms with higher social scores tend to pay higher wages. Improved employee motivation may further contribute to better financial performance. The regressions including industry dummy variables were estimated, grouping firms with negative coefficients separately from those with positive coefficients.

Table 21. Firm-fixed effect with growth rate of wages and average of social score and control variables

Wages	Coefficient	Standard Error	P-Value
Social score	2230.919	5033.831	0.6579
Size (Total Assets)	-101559.2	60083.63	0.0920
CAPEX	51339.57	62563.37	0.4125
Constant	1280131.	1320360.	0.3330
Adjusted R-Squared	0.001756		
Total panel observations	316		

The shows a negative coefficient for the social score when using the time-fixed effects approach. The analysis results for this model are presented in Table 22. However, the adjusted R-squared is very low, explaining the regression poorly. Meanwhile, the size variable has a statistically positive impact on wages, while capital expenditure has a dragging effect, as expected.

Table 22. Time-fixed effect using social score and negative industry dummy variables

Wages	Coefficient	Standard Error	P-Value
Social score	-0.003225	0.000844	0.0001
Size (Total Assets)	0.098275	0.022169	0.0000
CAPEX	-0.065589	0.017548	0.0002
Constant	10.27507	0.303641	0.0000
Adjusted R-Squared	0.019048		
Total panel observations	1,434		

The shows a negative coefficient for the social score when using the time-fixed effect approach. The analysis results for this model are presented in Table 23. However, the coefficient for the social score is not statistically significant, while also having a very low R-squared at around 2%. Capital expenditure has a negative relationship with wages, while size shows a negative coefficient but is not statistically significant. Meanwhile, for the positive dummy variables, the industries were energy, finance, healthcare, and real estate.

Table 23. Time-fixed effect using social score and positive industry dummy variables

Wages	Coefficient	Standard Error	P-Value
Social score	-0.001159	0.001579	0.4631
Size (Total Assets)	-0.015083	0.012616	0.2323
CAPEX	-0.036643	0.018204	0.0445
Constant	12.82443	0.335747	0.0000
Adjusted R-Squared	0.017580		
Total panel observations	650		

When using the firm-fixed effect for those industries that show a negative coefficient, the social score's coefficient turns positive, confirming the previous results derived in the first hypothesis paper. The analysis results for this model are presented in Table 24. This clearly shows that when all observed and unobserved factors are considered in the regression, the level of wages increases in line with an increase in the social score. Meanwhile, the size and capital expenditure variables, despite showing a negative relationship with wages, are both insignificant.

Table 24. Firm-fixed effect using social score and negative industry dummy variables

Wages	Coefficient	Standard Error	P-Value
Social score	0.002403	0.001089	0.0275
Size (Total Assets)	-0.072046	0.050721	0.1557
CAPEX	-0.026087	0.033170	0.4318
Constant	13.08317	1.042408	0.0000
Adjusted R-Squared	0.628453		
Total panel observations	1,434		

Table 25. Firm-fixed effect using social score and positive industry dummy variables

Wages	Coefficient	Standard Error	P-Value
Social score	0.003871	0.001158	0.0009
Size (Total Assets)	0.040050	0.055827	0.4734
CAPEX	-0.012739	0.026346	0.6289
Constant	10.60105	1.345634	0.0000
Adjusted R-Squared	0.799280		
Total panel observations	650		

When firm-fixed effects are applied, the social score exhibits a positive and statistically significant relationship with wage levels across industries, with positive coefficients indicating higher employee satisfaction. The analysis results for this model are presented in Table 25. The model achieved an R-squared of approximately 80 per cent, reflecting its strong explanatory power. The control variables remain statistically insignificant, firm size is positively associated with wages, and capital expenditure shows a negative relationship. Notably, the firm-fixed effects model produces the highest R-squared among all specifications, suggesting that unobserved firm-level heterogeneity is important. In contrast, the time-fixed and industry-fixed effects models indicate a negative relationship between ESG/Social scores and wages. Overall, the firm-fixed effects results provide the most reliable evidence that stronger social performance translates to higher employee compensation.

5. Discussion

The positive relationship between ESG Social scores and the employee wages in Time-Fixed model and Industry-Fixed model, but not in the firm-fixed effect model, is significant to both the empirical and theoretical literature on shareholder vs. stakeholder theories of the firm. The negative coefficient of the social score in the time-fixed and industry-fixed effect model makes a shallow sense through the line of argument that the shareholder theory would argue that ESG expenditure will lose resources to non-value as well as value generating activities like employee remuneration (Friedman 1962). The very large adjusted R-squared of such specifications (under 25 percent even with controls) which the estimates only account a small part of the actual wage variation among workers is undermined by the fact that it cannot reliably be relied upon to provide information about the causal Social score-wage relationship.

The high and statistically significant value of the firm-fixed effect model Social score coefficient is consistent with the claims of the stakeholder theory (Freeman 1984; Carroll 1999) and is reminiscent of the findings of Edmans (2011) who found that the largest drivers of the Social score- This finding is in line with Eccles et al. (2014) who show that financial payoffs of high-sustainability firms in the long-run are realized at the firm level but would be disguised when comparing across cross-sections. The heterogeneity within the sector is consistent with the ESG materiality framework suggested by Khan (2016), sectors, such as energy, financials, healthcare and real estate, where employee relations and quality of human capital can have a material effect on financial performance, have the strongest positive Social score-wage relationship, and labour-intensive low-margin sectors, such as consumer discretionary and industrials

Another methodological implication of the sign reversal is related to attempting to investigate the correlation of ESG and employees: both pooled OLS and cross-sectional designs will be prone to systematically creating biased inferences when attempting to determine the relationship between ESG and employees. The same applies to the case of researchers that assume that industry-average or country-level ESG data are proxies of firm social performance. The current paper reveals that the firm-fixed effect estimator is required in order to establish the genuine within-firm Social score-wage relation, in line with the methodological advice of Stock and Watson (2015) that panel studies of corporate social performance need to regulate the unobserved heterogeneity of firms. Finally, that the positive association between Social score and wage exists in the overall firm-fixed effect sample (which is both significant and robust) and that it also exists in either of the industry subsamples suggests the conviction of the robustness of the result and diminishes the possibility of the association being caused by outliers or modelling specification choices.

6. Policy and managerial implications

The findings of this study provide important implications for corporate managers, institutional investors, regulators, and policymakers operating in Europe. In an era characterized by the widespread adoption of digital corporate reporting and sustainability disclosures, information related to the social dimension of ESG should be regarded not merely as a regulatory requirement but also as a strategic element that supports employee well-being and strengthens corporate competitiveness. The findings obtained from the firm-fixed effects model indicate that firms with higher ESG Social scores tend to increase employee compensation over the long term. This result suggests that sustainable investments in employee welfare should not be viewed solely as part of corporate social responsibility initiatives but rather as long-term strategic investments in human capital. Accordingly, corporate boards and human resource committees should establish measurable targets related to living wages, pay equity, occupational health and safety, employee development, and training investments, and regularly disclose these indicators through digital sustainability reporting systems. In particular, the detailed social sustainability disclosures required under the European Union Corporate Sustainability Reporting Directive (CSRD) demonstrate that digital corporate reporting has become an important governance mechanism for improving employee welfare.

Another important finding of this study is that the relationship between ESG Social scores and employee compensation varies considerably across industries. In particular, this relationship is stronger among firms operating in the energy, financial, healthcare, and real estate sectors. This finding suggests that human capital constitutes one of the primary determinants of sustainable competitive advantage in knowledge-intensive industries. Consequently, firms operating in these sectors should communicate employee welfare indicators not only within their internal management processes but also more comprehensively and transparently through digital ESG reporting platforms and sustainability reports. Such an approach would enable investors to assess firms' social sustainability performance more accurately while simultaneously enhancing corporate credibility through greater digital transparency.

From the perspective of policymakers and ESG rating agencies, current social ESG indicators should be supported by more detailed and standardized digital reporting frameworks. At present, many ESG rating systems aggregate numerous social indicators, including employee compensation, pay inequality, employee turnover, training investments, and employee satisfaction, into a single composite score. This aggregation limits the ability to evaluate firms' actual social performance in a comprehensive manner. Therefore, in line with European Union regulations, companies should be encouraged to disclose indicators such as median employee wages, wage distribution, employee turnover rates, training investment per employee, and occupational health and safety performance through standardized digital sustainability reporting systems. More comprehensive digital ESG disclosures would improve not only the quality of academic research but also the ability of regulators and investors to conduct more accurate assessments.

Finally, institutional investors and portfolio managers should move beyond relying solely on aggregate ESG scores and instead evaluate the underlying indicators that constitute the social dimension of ESG separately. With the rapid development of digital ESG data platforms, investors now have access to significantly more detailed information regarding firms' social performance. Consequently, investors should engage more actively with corporate management regarding the quality of social sustainability practices, employee welfare policies, and the quality of digital sustainability reporting. Such an approach would not only improve investment decision-making but also encourage firms to adopt more transparent digital sustainability reporting practices, stronger employee welfare policies, and more sustainable long-term value creation.

7. Limitations and future research

This study has several limitations that provide opportunities for future research. First, employee welfare is measured solely by average wages. However, employee welfare encompasses multiple dimensions beyond monetary compensation, including fringe benefits, job security, psychological well-being, employee satisfaction, turnover, and absenteeism. Therefore, future studies should employ more comprehensive measures of employee welfare to provide a more nuanced understanding of the relationship between the social dimension of ESG and employee well-being.

Furthermore, the analysis is limited to firms included in the S&P Europe 350 Index, restricting the generalizability of the findings to other institutional and regulatory environments. Although Europe represents one of the most advanced regions in terms of sustainability regulations and ESG implementation, future research should examine multi-regional or global samples, including both developed and emerging economies, to compare the effects of social ESG performance across different institutional contexts.

Another limitation relates to data availability. Due to data constraints, important firm-specific variables such as research and development (R&D) expenditures could not be incorporated into the empirical model. The omission of these variables may introduce omitted variable bias. Future studies are therefore encouraged to include additional firm characteristics, such as R&D investment, innovation capacity, digital transformation, and technology investment, to provide a more comprehensive explanation of the relationship between social ESG performance and employee welfare.

In addition, the Refinitiv Social score employed in this study may indirectly incorporate certain wage-related indicators, creating a potential measurement overlap. Future research could improve the robustness of the findings by utilizing alternative ESG data providers, such as MSCI or Sustainalytics, or by adopting adjusted social ESG indices that exclude compensation-related components. Moreover, comparing ESG indicators obtained from different digital ESG data platforms would contribute to a better understanding of the consistency, reliability, and transparency of digital sustainability reporting.

Finally, the panel dataset used in this study is unbalanced, with the number of observations varying across years, which may reduce the statistical power of the empirical analysis. Moreover, the sample period ends in 2020 and therefore does not capture the post-COVID-19 recovery period or the implementation of recent European sustainability regulations, particularly the Corporate Sustainability Reporting Directive (CSRD). Future research should extend the sample period and investigate how digital ESG reporting systems, digital corporate disclosures, and AI-assisted ESG assessment mechanisms influence employee welfare, compensation policies, and corporate performance. Such studies would provide valuable insights into the evolving intersection of sustainability and digital corporate transformation.

Declaration of competing interest

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

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