Journal of Sustainable Digital Futures

JSDF

Journal of Sustainable Digital Futures

YEAR: 2025 VOLUME: 1 ISSUE: 2 ISSN: 3108-446X

www.jsdf.org.tr

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Vizyon Education and Consultancy Association

JOURNAL OF SUSTAINABLE DIGITAL FUTURES

E-ISSN: 3108-446X

Volume: 1, Issue: 2, Year: 2025

Owner

Vizyon Education and Consulting Association

(Vizyon Eğitim ve Danışmanlık Derneği)

Chief Editor

Prof. Dr. Mesut DOĞAN

Contact

Journal of Sustainable Digital Futures (JSDF)

E-mail: jsdfutures@gmail.com

Web: https://jsdf.org.tr/

Publisher

Vizyon Education and Consulting Association – Antalya, Türkiye

JOURNAL OF SUSTAINABLE DIGITAL FUTURES

Year: 2025 - Volume: 1 - Issue: 2

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CONTENTS

Journal of Sustainable Digital Futures 2025 1(2)

Journal of Sustainable Digital Futures

journal homepage: https://jsdf.org.tr/

Nonlinear sustainable outcomes of digitalization in Türkiye: A modified cross quantile regression perspective

Hafidha LAHMERI[1]

HIGHLIGHTS

[1] Mascara University, Local Community management and Local Development Laboratory, Algeria, hafidha.lahmeri@univ-mascara.dz

ARTICLE INFO

Keywords:

Digitalization
Carbon emissions
Sustinable environmental management
Türkiye

ABSTRACT

This study examines the effects of different types of digitalization on sustainable environmental management using quarterly data for Türkiye covering the period 1993-2023. Internet use, mobile subscriptions, and fixed line subscriptions are employed as the main indicators representing digitalization, while carbon emissions serve as the measure of environmental quality. To capture the relationships between variables across different points of the distribution, the Cross-Quantile Regression (CQR) method is applied, and the robustness of the findings is further assessed using Modified Quantile Regression (MQR) and Quantile on Quantile Kernel Regularized Least Squares (QQ-KRLS). The results indicate that internet use negatively affects environmental quality particularly in the lower carbon emission quantiles. However, as emission levels rise, the impact of internet penetration weakens considerably and becomes statistically insignificant in the higher quantiles. Mobile subscriptions are found to deteriorate environmental quality most notably in the middle quantiles, whereas the effects at the lower and upper quantiles remain limited. In contrast, fixed line subscriptions generally reduce carbon emissions, with this beneficial effect becoming more pronounced in the medium and high emission quantiles. These findings demonstrate that the environmental effects of different digitalization types are not homogeneous; rather, they vary depending on the emission level and display a nonlinear structure.

1. Introduction

Digitalization transforms the functioning of economic and social systems, generating multidimensional effects on environmental sustainability. As digital technologies reshape energy use patterns, production processes, and consumer behaviors, the role of the digital economy in environmental quality has become increasingly central (Ullah et al. 2024; Tekbaş and İslamoğlu 2025). This transformation not only accelerates information flows but also creates new opportunities for monitoring, measuring, and managing environmental risks. The strengthening of digital infrastructures supports the development of systems that enable more precise monitoring of carbon emissions and energy consumption. Through big data analytics, sensor networks, and smart city technologies, environmental indicators can be tracked in real time, enhancing environmental management capacity (Yang et al. 2022; Ma and Wu 2022). As evidenced in digital city applications, digitalization accelerates policy interventions by improving the flow of environmental information.

Received 06 December 2025; Received in revised from 24 December 2025; Accepted 28 December 2025
Available online 30 December 2025

Digitalization also enhances efficiency in production processes, contributing to the reduction of environmental pressures. Industrial digitalization, automation, and robotics can lower carbon intensity, particularly in energy intensive sectors (Yao et al. 2024; Jingren et al. 2025). Increasing digital inputs in production offers the possibility of generating the same output with lower energy costs, thereby improving carbon productivity (Tang et al. 2023).

The environmental impact of digitalization exhibits heterogeneity across sectors. While certain components of the digital economy, such as data centers, mobile communication networks, and high-density digital infrastructures, may increase energy demand (Zhang and Wang 2023; Du and Wang 2024), fixed line infrastructures or optimized digital processes tend to exhibit relatively lower carbon effects (Pan et al. 2023). Thus, the environmental influence of digitalization is far from linear and varies depending on the type of digital technology deployed. Another dimension of digital transformation relates to improving organizational sustainability performance. The integration of digital technologies into supply chains facilitates the monitoring of environmental impacts at every stage of production and distribution, aiding firms in meeting carbon neutral objectives (Li et al. 2025; Chu et al. 2023). By enhancing governance capacity, digitalization strengthens transparency and accountability mechanisms, thereby supporting more effective environmental decision making.

Digitalization also has a transformative effect on individual behavior. The widespread use of digital platforms fosters environmentally conscious consumption habits and increases awareness of low-carbon choices (Zhang et al. 2020; Xie 2024). Enhanced information flow in the digital environment raises societal awareness and encourages the adoption of sustainable lifestyles. Overall, digitalization is a multidimensional transformation tool that contributes to environmental sustainability both directly and indirectly. While the expansion of the digital economy holds the potential to improve environmental performance, some components may increase energy demand and create environmental trade-offs. Consequently, assessing the digitalization-environment nexus requires a flexible and comprehensive framework that accounts for the type of digitalization, energy infrastructure, and country specific conditions (Škare et al. 2024; Brenner and Hartl 2021).

The primary objective of this study is to reveal the effects of different dimensions of digitalization on environmental quality in Türkiye and to empirically assess the role of digital transformation in sustainable environmental management. The relationships between carbon emissions and the components of digitalization, namely internet usage, mobile subscriptions, and fixed line subscriptions, are examined within a holistic framework that considers different points of the distribution. In this context, the study aims to make the heterogeneous and regime dependent nature of the digitalization and environment nexus visible, at a time when most of the literature relies on linear models.

The empirical analysis employs the Cross Quantile Regression (CQR) method, which allows measurement of how the relationship between variables changes across different emission levels. Unlike traditional mean based approaches, CQR incorporates the full distribution of the independent variables and reveals how relationships differ across both lower and upper quantiles. To evaluate the robustness of the findings, Modified Quantile Regression (MQR) and Quantile on Quantile Kernel Regularized Least Squares (QQKRLS) methods are also implemented, enabling the nonlinear structure of the relationships to be tested within multiple econometric frameworks. The study uses quarterly data for Türkiye covering the period 1993 to 2023.

The primary motivation of this study stems from the fact that the existing literature contains very few studies that examine the effects of different dimensions of digitalization on environmental quality in the context of Türkiye using a quantile based perspective. The digitalization environment nexus has predominantly been analyzed through linear and mean based approaches; however, such methods largely overlook the reality that the environmental impacts of digitalization may vary depending on emission levels, economic structure, and the intensity of technological usage. In contrast, the environmental consequences of digital technologies may emerge in a nonlinear and heterogeneous manner through channels such as energy demand, production efficiency, and the structure of communication infrastructure. This gap is even more pronounced in the context of Türkiye. While Türkiye has experienced a rapid digital transformation over the past three decades, it has simultaneously faced increasing energy demand and environmental pressures. Despite this, the conditions under which different forms of digitalization (such as internet usage, mobile communication, and fixed line infrastructure) generate adverse or favorable effects on environmental quality have not been sufficiently analyzed. Existing studies generally represent digitalization with a single indicator and fail to account for country specific structural dynamics. Aiming to fill this gap, the present study employs modern quantile based econometric methods that examine the environmental effects of digitalization across the entire distribution. Through the use of CQR, MQR, and QQKRLS approaches, the study enables a detailed assessment of how the impacts of digitalization on environmental quality differ across low, medium, and high emission levels. Unlike conventional models that focus solely on average effects, these methods make it possible to uncover the nonlinear, regime dependent, and asymmetric nature of the relationships.

Within this framework, the findings expected to be obtained from the study are anticipated to demonstrate that the environmental impacts of digital infrastructure investments and communication technologies are shaped not by a uniform and linear structure, but rather through multiple channels and under varying conditions. This perspective allows for a more nuanced evaluation of the circumstances under which digitalization may exert either positive or negative effects on environmental quality through mechanisms such as energy consumption, carbon intensity, and patterns of technological use. This approach offers an analytical framework that can contribute to the design of digital transformation strategies that are more closely aligned with environmental sustainability objectives from a policymaking perspective. In particular, indicators derived from quantile based analyses are expected to reveal the levels at which digitalization has the potential to intensify or alleviate environmental pressure, thereby providing guidance for the development of sustainable digital transformation policies that are more targeted, flexible, and context specific.

This study is organized into seven sections. Following the introduction, the second section summarizes the literature on the relationship between digitalization and environmental quality. The third section presents the data set and the methodology in detail, while the fourth section reports the empirical findings. The fifth section discusses the results, and the sixth section provides policy recommendations. The seventh and final section outlines the limitations of the study and offers suggestions for future research.

2. Literature review

The body of research examining the relationship between digitalization and environmental quality has expanded rapidly in recent years at both the macroeconomic and sectoral levels. Evidence from OECD and other developed countries demonstrates that digitalization affects environmental quality through both direct and indirect channels. For example, Ullah et al. (2024) investigate the impact of digitalization, technological innovation, and financial innovation on environmental quality within an N-shaped EKC framework for OECD countries, showing that beyond certain thresholds, digitalization can play an emission reducing role. Similarly, Yu and Liu (2024), using data for 136 countries, find that digital transformation can align with environmental efficiency under appropriate institutional and technological conditions. Ni et al. (2022) and Škare et al. (2024) analyze digitalization from the perspective of ecological footprint and load capacity factors, emphasizing that natural resource use, governance quality, and digital infrastructure jointly shape sustainable growth trajectories.

Country and region specific studies reveal that the digitalization environment relationship is context dependent and largely nonlinear. Ma and Wu (2022) show that smart city applications in China may improve energy efficiency, yet poorly designed digital infrastructure can also intensify environmental pressure. Du and Wang (2024) and Yang et al. (2022) find that China's digital economy has the potential to reduce carbon intensity, although the magnitude of the effect varies by region and industrial structure. Adha et al. (2023) for Taiwan and Onyeneke et al. (2024) for Africa document that ICT and renewable energy consumption influence carbon emissions jointly, indicating that digitalization contributes to environmental gains only when assessed together with the energy mix and climate policies.

Studies focusing on sectoral effects show that digitalization has heterogeneous environmental implications across manufacturing, agriculture, animal husbandry, construction, and supply chains. Tang et al. (2023), Fang et al. (2022), and Zhang et al. (2023) examine input digitalization in the manufacturing sector, finding that digital technologies reduce carbon emission intensity through process optimization, although the effect may remain limited in energy intensive subsectors. Zhao et al. (2023) and He et al. (2025) highlight the potential of digital tools to lower carbon intensity in agriculture and animal husbandry, while Niu et al. (2025) analyze the effect of digital inputs on CO2 emissions in

China's construction sector under the dual carbon policy framework. Li and Liao (2022) and Ma et al. (2023) emphasize the synergistic effects of digitalization and industrialization on total factor carbon performance, whereas Li et al. (2025) examine the role of supply chain digitalization in carbon neutral management.

Firm level studies provide evidence that enterprise digital transformation reduces emissions and affects micro level efficiency dynamics. Shang et al. (2023) and An and Shi (2023) show that digital transformation decreases firm level carbon emissions, while Sun et al. (2025) analyze the interaction between digitalization and carbon reduction technology R&D within a Stackelberg framework. Chu et al. (2023) highlight the role of intelligent device utilization in emission reduction, and Yao et al. (2024) demonstrate how industrial robots support net zero targets. Li et al. (2022) and Ma et al. (2023) further document the combined influence of digitalization and industrial restructuring on carbon performance.

Another strand of literature investigates the digitalization-environment relationship in the context of energy use, trade, and global value chains. Zhang and Wang (2023) analyze digitalization, electricity consumption, and CO2 emissions in the manufacturing industry, while Huang and Zhang (2023) explore how digitalization affects carbon emissions embodied in exports through global value chain positioning. Ke et al. (2022) and Saqib et al. (2023) examine digitalization together with trade, financial development, and renewable energy within the EKC framework, offering insights into the pollution haven hypothesis and ecological footprint dynamics.

Studies such as Zhang et al. (2020), Pan et al. (2023), and Wang and Xu (2021) evaluate the relationship between internet use, human capital, and individuals' environmental perceptions, showing that digitalization influences environmental quality not only through technical mechanisms but also via behavioral and cognitive channels. Goethals and Ziegelmayer (2024), Xie (2024), and Brenner and Hartl (2021) examine environmental concerns, willingness to pay for low carbon electricity, and the links between digitalization and ecological, economic, and social sustainability.

In relation to Türkiye and similar economies, this literature indicates that digitalization does not have a uniform or one directional effect on environmental quality. The magnitude and direction of the impact vary according to country groups, sectors, types of digital infrastructure, energy composition, and institutional frameworks. Considering evidence from OECD, Asian, African, European, and American contexts collectively, digitalization can offer significant opportunities for reducing carbon emissions and ecological footprints when supported by appropriate energy policies, green innovation, financial development, and governance. Otherwise, digitalization may increase environmental pressure through higher energy consumption and production scale. This multidimensional and context sensitive structure highlights the importance of considering nonlinear and heterogeneous effects when modeling the digitalization environment relationship empirically.

Although the existing literature demonstrates that the relationship between digitalization and environmental quality varies significantly across country groups, sectors, types of digital infrastructure, and institutional frameworks, studies that examine this relationship specifically for Türkiye, by disentangling different dimensions of digitalization, and across the entire distribution remain highly limited. In particular, most empirical studies rely on linear or mean based models when assessing the environmental impacts of digitalization, an approach that is insufficient for capturing asymmetric, nonlinear, and regime dependent effects that vary with emission levels.

Moreover, the literature largely overlooks comparative analyses of how different components of digitalization, such as internet usage, mobile communication, and fixed line infrastructure, affect environmental quality within the same country context and under a unified empirical framework. Given Türkiye's rapid digital transformation alongside increasing energy demand and environmental pressures, there is a clear need for empirical evidence that identifies the conditions under which digitalization exerts either mitigating or aggravating effects on environmental quality using quantile based methodologies. In this context, the present study aims to fill an important gap in the literature by explicitly accounting for heterogeneity and nonlinearity in the digitalization-environment nexus within the Turkish context.

3. Data and methodology

3.1. Data

The main purpose of this study is to comprehensively analyze the effects of different dimensions of digitalization on environmental sustainability in Türkiye. In the study, digitalization is represented through three indicators: internet usage rate (INTERNET), mobile cellular subscriptions (MOBILE), and fixed telephone subscriptions (FIXED). These indicators reflect the multidimensional structure of digitalization, capturing both modern and traditional communication technologies. The analysis is based on quarterly data for the period 1993-2023 for Türkiye, and this long term, high frequency dataset allows for a detailed examination of the dynamic relationship between digitalization and carbon emissions (CO).

Türkiye was selected as the focus of the analysis primarily because the country has undergone rapid transformation in both its digital infrastructure and economic structure over the past three decades. During this period, internet penetration has increased significantly, mobile communication usage has become widespread, and the share of the digital services sector has considerably expanded. At the same time, Türkiye's energy consumption and carbon emissions have risen substantially. Therefore, the direction and magnitude of the relationship between digitalization and environmental pressure constitute a critical area of inquiry for Türkiye from both economic and policy perspectives. In this context, the study aims to provide a current and country specific contribution to the literature by revealing whether digitalization has an improving or worsening effect on environmental quality.

Table 1. Variable definitions and data sources

Code	Variable name	Measurement	Source
CO	CO_2 emissions	Carbon dioxide (CO2) emissions (t CO2e/capita)	WDI
INTERNET	Digitalization-1	Individuals using the Internet (% of population)	WDI
MOBILE	Digitalization-2	Mobile cellular subscriptions (per 100 people)	WDI
FIXED	Digitalization-3	Fixed telephone subscriptions (per 100 people)	WDI

Table 1 summarizes the variables used to examine the relationship between carbon emissions and digitalization in the study. While the dependent variable CO_2 emissions represents Türkiye's environmental performance, the INTERNET, MOBILE, and FIXED variables reflect different dimensions of digitalization. Internet usage captures the level of modern digital transformation, mobile subscriptions indicate the widespread use of digital communication, and fixed telephone subscriptions represent the presence of more traditional communication infrastructure. The fact that all data are obtained from the World Bank provides a reliable and comparable dataset for the analysis. Within this framework, the study allows for a multidimensional evaluation of the effects of digitalization on environmental quality.

In this study, the level of digitalization is proxied by individuals using the Internet (% of population) (INTERNET), mobile cellular subscriptions (per 100 people) (MOBILE), and fixed telephone subscriptions (per 100 people) (FIXED), which are widely accepted and commonly used indicators in the literature to capture digital infrastructure, access, and usage dimensions. A substantial body of empirical research examining the environmental and sustainability impacts of digitalization conceptualizes digitalization as a multidimensional phenomenon and employs internet usage and mobile communication indicators as core explanatory variables. For instance, Jóźwik et al. (2023) and Altay Topcu (2025) utilize internet usage and ICT related indicators to investigate the direct and indirect effects of digitalization on environmental quality and green growth. Similarly, Tekbaş and İslamoğlu (2025) and Ullah et al. (2024) rely on internet and mobile communication indicators when assessing the role of digitalization in sustainable environmental management and energy environment relationships. Mobile cellular subscriptions, in particular, are frequently used as a proxy for digital inclusion and technological diffusion, as demonstrated by Ratombo and Mongale (2024) and Ehigiamusoe et al. (2025) in studies focusing on the economic and energy related dimensions of digitalization. Fixed telephone subscriptions, on the other hand, reflect the structural and infrastructural foundations of information and communication technologies and are included within composite digitalization frameworks in studies such as Elom et al. (2024) and Azu et al. (2024), which examine the socioeconomic implications of communication infrastructure. Therefore, the digitalization variables employed in this study are not arbitrarily selected but are firmly grounded in established theoretical and empirical practices in the literature, aiming to comprehensively capture multiple dimensions of digitalization.

3.2. Methodology

To prevent spurious regressions, the analysis first applies the Quantile Augmented Dickey-Fuller (QADF) test, which examines stationarity across different points of the conditional distribution rather than only at the mean. This allows the test to capture heterogeneity and potential nonlinear persistence in the data. Model adequacy is then evaluated using the Brock-Dechert-Scheinkman (BDS, 1996) test on the residuals. Rejecting the i.i.d. assumption indicates nonlinear dependence or omitted dynamics that linear models cannot detect. Thus, while QADF determines the integration order of the variables, the BDS test verifies whether the residuals satisfy independence. The BDS statistic is calculated as follows in Equation (1), Equation (2) and Equation (3), respectively:

$$qcov_{\tau}(Y,X) = cov\left\{I\left(Y - Q_{\tau,Y} > 0\right), x\right\} = E(\varphi_{\tau}(Y - Q_{\tau,Y})(X - E(X)) \tag{1}$$

$$\varphi_{\tau}(w) = \tau - I(w < 0) \tag{2}$$

$$W_m(\epsilon) = \frac{\hat{c}_m(\epsilon) - \hat{c}_1^m(\epsilon)}{\sigma_m(\epsilon)} \tag{3}$$

Sim and Zhou’s (2015) quantile on quantile regression (QQR) models the interaction between the quantiles of two variables, but the method is highly bandwidth dependent and often suffers from singular matrix problems. In addition, QQR lacks a formal statistical inference framework (Adebayo et al. 2025). To address these drawbacks, Li (2024) developed Cross Quantile Regression (CQR), which constructs quantile series for both the dependent and independent variables and then estimates regressions across all quantile combinations. The general structure of CQR is presented in Equation (4).

$$Q_{\tau}(Y) \;=\; \Upsilon_0(\tau,\theta) \;+\; \Upsilon_1(\tau,\theta)\, Q_{\theta}(X) \;+\; \varepsilon(\tau,\theta) \tag{4}$$

CQR improves upon standard quantile regression by modelling how different quantiles of the explanatory variable influence the full distribution of the dependent variable. This approach uncovers tail interactions and asymmetric dependence patterns that conventional methods cannot reveal, showing how shocks at specific quantiles of X propagate across multiple quantiles of Y (Adebayo et al. 2025).

As a robustness check, the study applies the Quantile on Quantile Kernel Based Regularized Least Squares (QQKRLS) method. KRLS, originally developed by Hainmueller and Hazlett (2014), is a flexible machine-learning estimator that avoids strict functional form assumptions. Using Gaussian kernels, it captures nonlinear and heterogeneous effects, and evaluates the influence of X on Y through pointwise marginal effects, summarised in Equation (5).

$$E_N\left[\frac{\widehat{\beta Y}}{\beta X_k}\right] = \frac{-2}{\sigma^2 N}\sum_k \sum_i j_i e^{\frac{\|x_i - x_k\|^2}{\sigma^2}}(X_i - X_k) \tag{5}$$

The standard KRLS method models only the distribution of the dependent variable and evaluates nonlinear effects using an average marginal impact, without accounting for the full distribution of the predictor. To address this limitation, QQKRLS extends KRLS by incorporating quantiles of both the dependent and independent variables, allowing joint estimation of effect size and significance across the entire distribution (Adebayo et al. 2024). Thus, QQKRLS enables a more comprehensive assessment of how X influences Y, as shown in Equation (6).

$$E_N\left[\frac{\beta\hat{Q}Y_\tau}{\beta QX_{\theta k}}\right] = \frac{-2}{\sigma^2 N}\sum_k \sum_i j_i e^{\frac{-\|X_{\theta i}-X_{\theta k}\|^2}{\sigma^2}}(X_{\theta i} - X_{\theta k}) \quad (6)$$

4. Empirical results

In this part of the study, the empirical findings on the effects of different types of digitalization on sustainable environmental management in Türkiye are presented. Before the main analysis, the QADF stationarity test and the BDS nonlinearity test were applied to assess the structural properties of the series. Following these preliminary tests, the relationships between the variables were examined using the Cross Quantile Regression (CQR) approach, which reveals asymmetric and distribution dependent effects. Finally, to evaluate the robustness of the results, additional analyses based on the Modified Quantile Regression (MQR) and the Quantile on Quantile Kernel Regularized Least Squares (QQKRLS) methods were conducted.

Table 2. Descriptive Statistics

	CO	INTERNET	MOBILE	FIXED
Mean	4.078603	34.18429	62.1185	20.86774
Median	4.215612	34.37	86.6345	21.5
Maximum	5.474392	85.9607	105.684	28.5
Minimum	2.725375	0.00846	0.146933	11.4
Std. Dev.	0.861249	29.68826	38.77622	5.822278

Table 2 presents the overall distribution of the variables used in the analysis. The relatively limited volatility in the carbon emissions (CO) variable indicates that environmental pressure in Türkiye did not exhibit major fluctuations over the examined period. In contrast, the digitalization indicators (INTERNET, MOBILE, FIXED) show a wide range of variation, particularly in internet usage and mobile subscriptions. This reflects the rapid pace of digital transformation in Türkiye throughout the study period. The substantial rise in mobile usage, along with the relatively narrow variation in fixed line subscriptions, illustrates a shift from traditional communication infrastructure toward a more mobile centered structure. Overall, the descriptive statistics demonstrate that Türkiye's dynamic digitalization process provides an important analytical basis for assessing environmental outcomes.

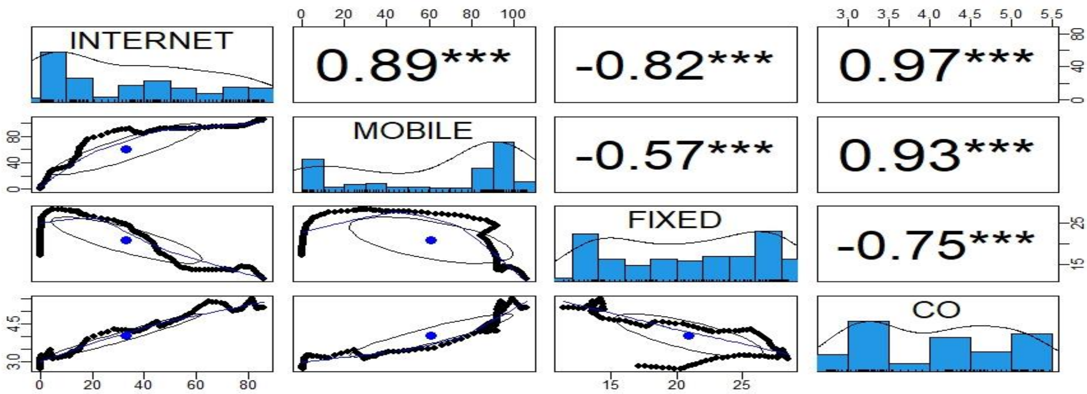


Figure 1. Correlations matrix

Figure 1 presents the correlation matrix and shows clear relationships among the variables. Internet use, mobile subscriptions, and fixed line subscriptions all display strong and statistically significant correlations with carbon emissions. Internet and mobile usage are positively correlated with CO, while fixed line usage shows a negative correlation. This indicates that different types of digitalization have distinct environmental implications. Overall, the matrix demonstrates the presence of notable linear relationships among the variables, highlighting the importance of accounting for these dependencies in the empirical analysis.

Table 3. BDS test results

Dimension	CO	INTERNET	MOBILE	FIXED
m2	0.182381*	0.181112*	0.199873*	0.151227*
m3	0.301736*	0.292013*	0.335064*	0.235111*
m4	0.378295*	0.359375*	0.427757*	0.280184*
m5	0.427638*	0.397604*	0.491870*	0.298011*
m6	0.460516*	0.410732*	0.536176*	0.304430*

Note: *p < 1%

Table 3 BDS test results show that all variables exhibit statistically significant dependence across dimensions m2 to m6. These findings indicate that the CO, INTERNET, MOBILE and FIXED series are not independent and identically distributed (i.i.d.), meaning they contain nonlinear structures, complex dependencies or hidden dynamics. Therefore, linear models alone are insufficient to fully capture the behavior of these variables, and the use of more advanced nonlinear methods is required.

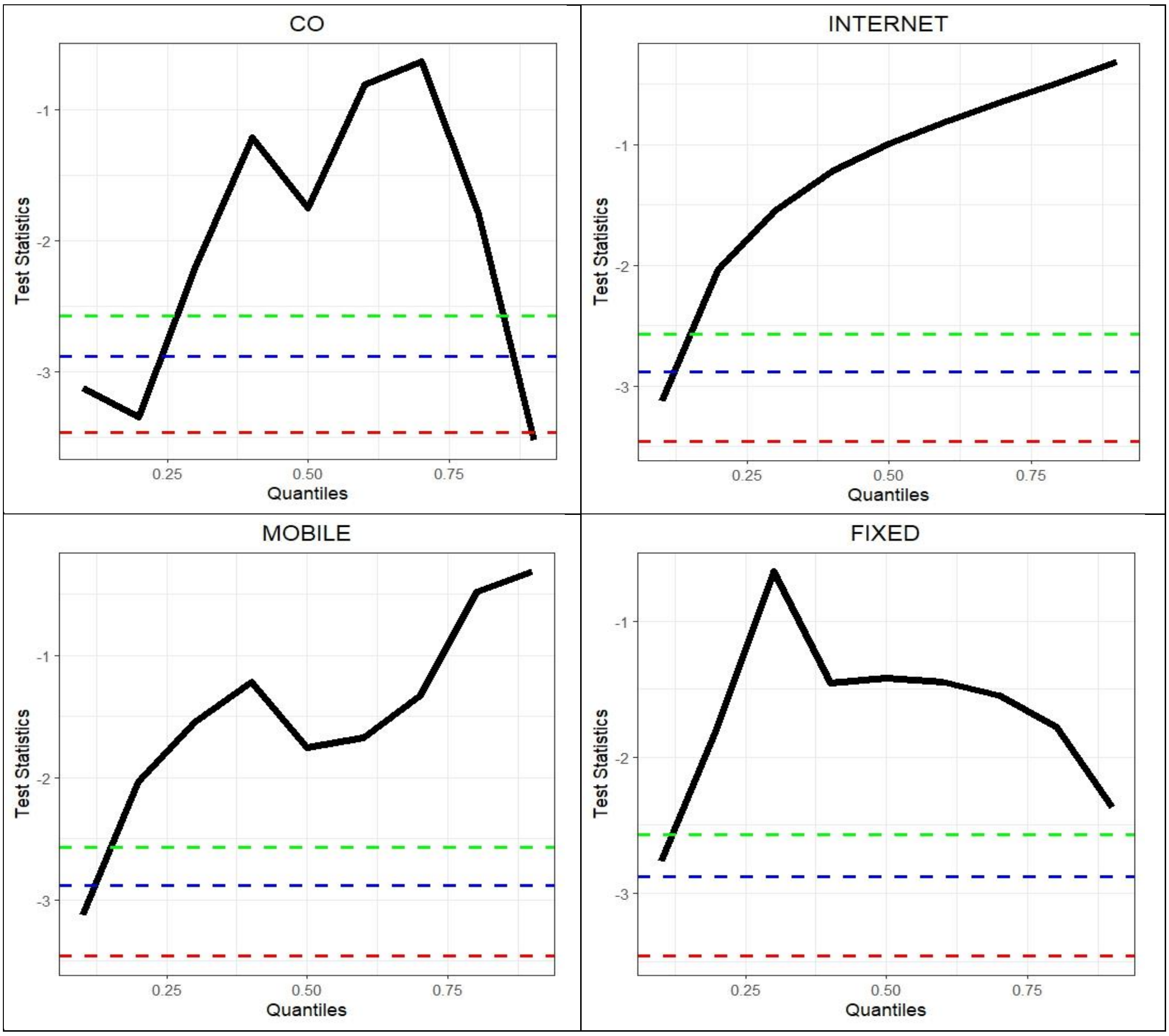


Figure 2. QADF unit root test

Figure 2 shows that the QADF unit root statistics exceed the critical threshold lines across most quantiles. This indicates that the variables contain unit roots at the corresponding quantile levels and are non stationary in levels. To ensure the reliability of the analysis and eliminate the risk of spurious regression, all variables were transformed into their first differences (I(1)) before proceeding to the next modeling steps. In this way, advanced quantile based methods such as CQR and QQKRLS were applied to stationary series, ensuring the validity and robustness of the empirical results.

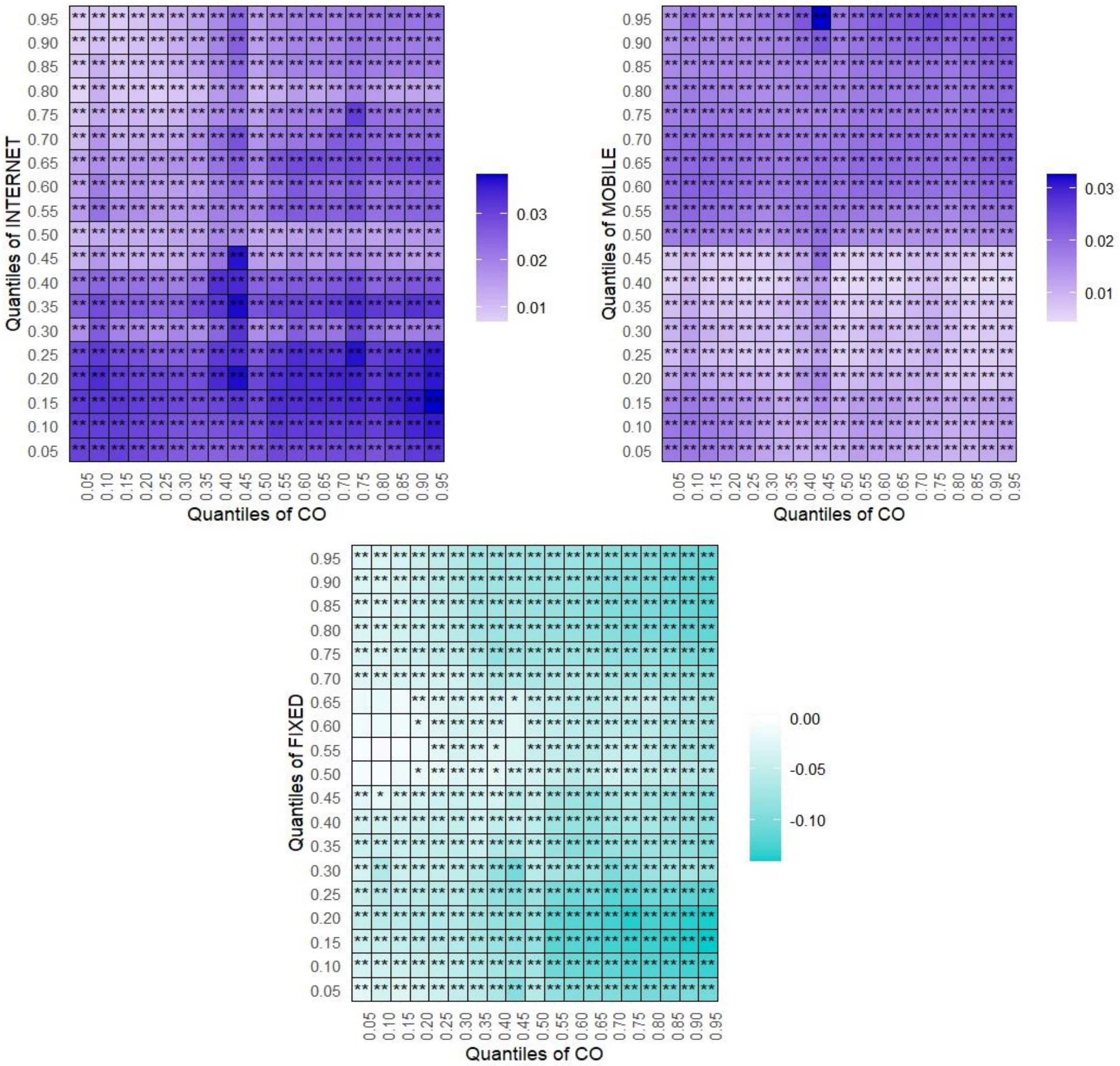


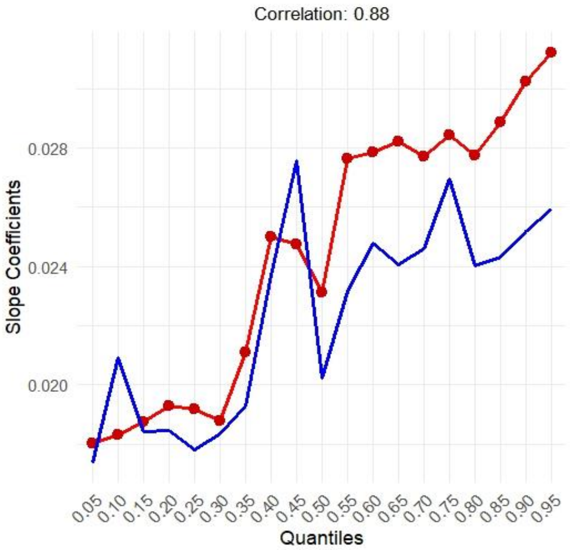
Figure 3. Cross quantile regression results

Figure 3 presents the Cross Quantile Regression results and shows that the relationship between different forms of digitalization and carbon emissions varies markedly across quantile levels. The findings for internet use indicate that the association is stronger at lower CO quantiles, suggesting that increases in internet penetration exert a more pronounced environmental impact when emissions are relatively low. As emission levels rise, the effect becomes weaker, implying that the marginal environmental influence of digital activities diminishes under high emission regimes. This pattern demonstrates that the environmental impact of internet use is nonlinear and sensitive to the prevailing level of emissions.

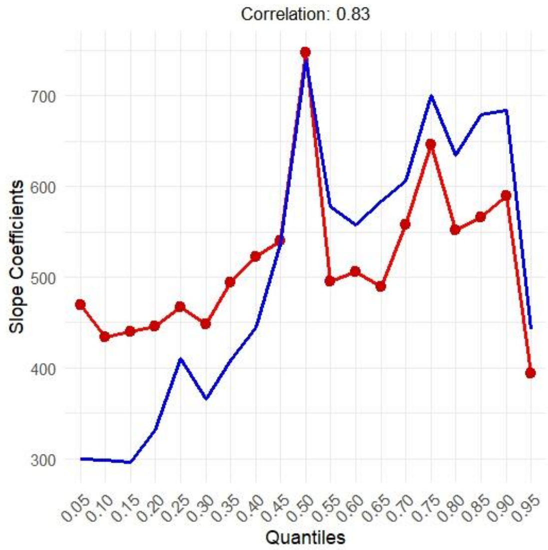
The results for mobile subscriptions show that the interaction with CO is strongest in the middle quantile ranges. This suggests that the expansion of mobile communication infrastructure may contribute more noticeably to environmental pressure under moderate emission conditions. In contrast, the weaker relationship observed at both lower and higher quantiles indicates that the environmental effect of mobile usage is heterogeneous across emission regimes and cannot be captured by a simple linear structure.

Fixed line subscriptions generally exhibit a negative association with carbon emissions. This relationship becomes more pronounced at medium and high CO quantile levels, indicating that increases in fixed line usage tend to reduce emissions, likely due to the relatively lower energy requirements of fixed line infrastructure compared to mobile technologies. The weaker effects observed at lower quantiles suggest that changes in fixed line usage have limited environmental consequences when emissions are already low.

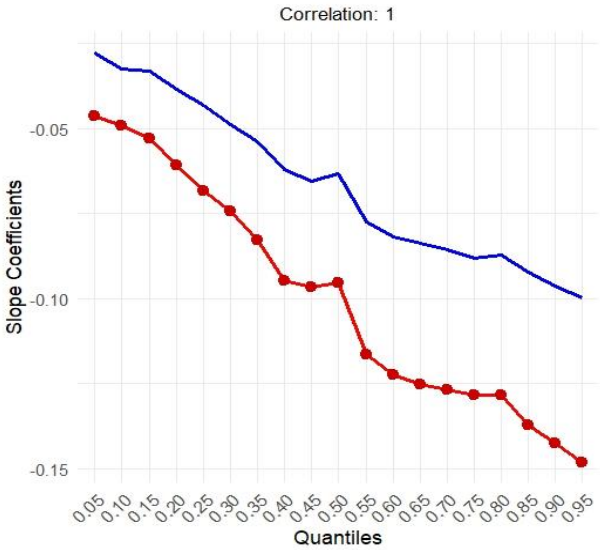
Overall, the results demonstrate that the environmental impact of digitalization depends both on the type of digital technology and on the position within the carbon emission distribution. Therefore, assessments of digital technologies in the context of environmental sustainability must consider these quantile dependent and asymmetric dynamics.



a) INTERNET



b) MOBILE



c) FIXED

Figure 4. MQR (red) and averaged CQR (blue) estimates

Figure 4 presents a comparative assessment of the slope coefficients obtained from the Modified Quantile Regression (MQR) and the Averaged Cross Quantile Regression (CQR) methods. For all three digitalization indicators, the correlation between the MQR and CQR slope series ranges between 0.83 and 1, indicating that the direction and general pattern of the relationship do not change depending on the estimation method and that the findings are highly consistent. While MQR captures sharper transitions—especially at the extreme quantiles—revealing regime shifts and threshold points more clearly, CQR provides a smoother representation of the same relationships and reliably reflects the overall direction of effects.

For INTERNET, the results show that the slope coefficients with CO increase across quantiles, and both methods capture this upward trend consistently. The strengthening effect of internet use on CO at higher emission quantiles becomes evident, with MQR capturing sharper rises and CQR presenting a stable upward pattern. This indicates that the environmental impact of internet usage is sensitive to emission intensity and displays an asymmetric structure. In the case of MOBILE, the results exhibit a similar pattern. The relationship with CO becomes stronger in the middle quantile ranges, with MQR identifying sharper jumps in specific bands. This suggests that mobile communication infrastructure generates a more pronounced environmental effect under certain emission regimes. The smoother CQR profile confirms the positive and quantile dependent structure of this relationship. For FIXED, both methods show a negative relationship with CO that intensifies across the quantiles. As fixed line usage increases, its reducing effect on emissions becomes stronger at higher emission quantiles. MQR captures sharper declines in these ranges, while CQR maintains the general downward pattern. The correlation coefficient of 1 indicates that the findings regarding fixed line usage are highly robust.

Overall, the combined evaluation of the MQR and CQR methods clearly shows that digitalization affects environmental outcomes in a quantile dependent and regime sensitive manner. While internet and mobile usage increase emissions, fixed line usage reduces them, and these effects are concentrated particularly in the upper emission quantiles. Therefore, policy design should jointly consider the general direction provided by CQR and the threshold specific intensities identified by MQR to effectively manage the net environmental consequences of digitalization.

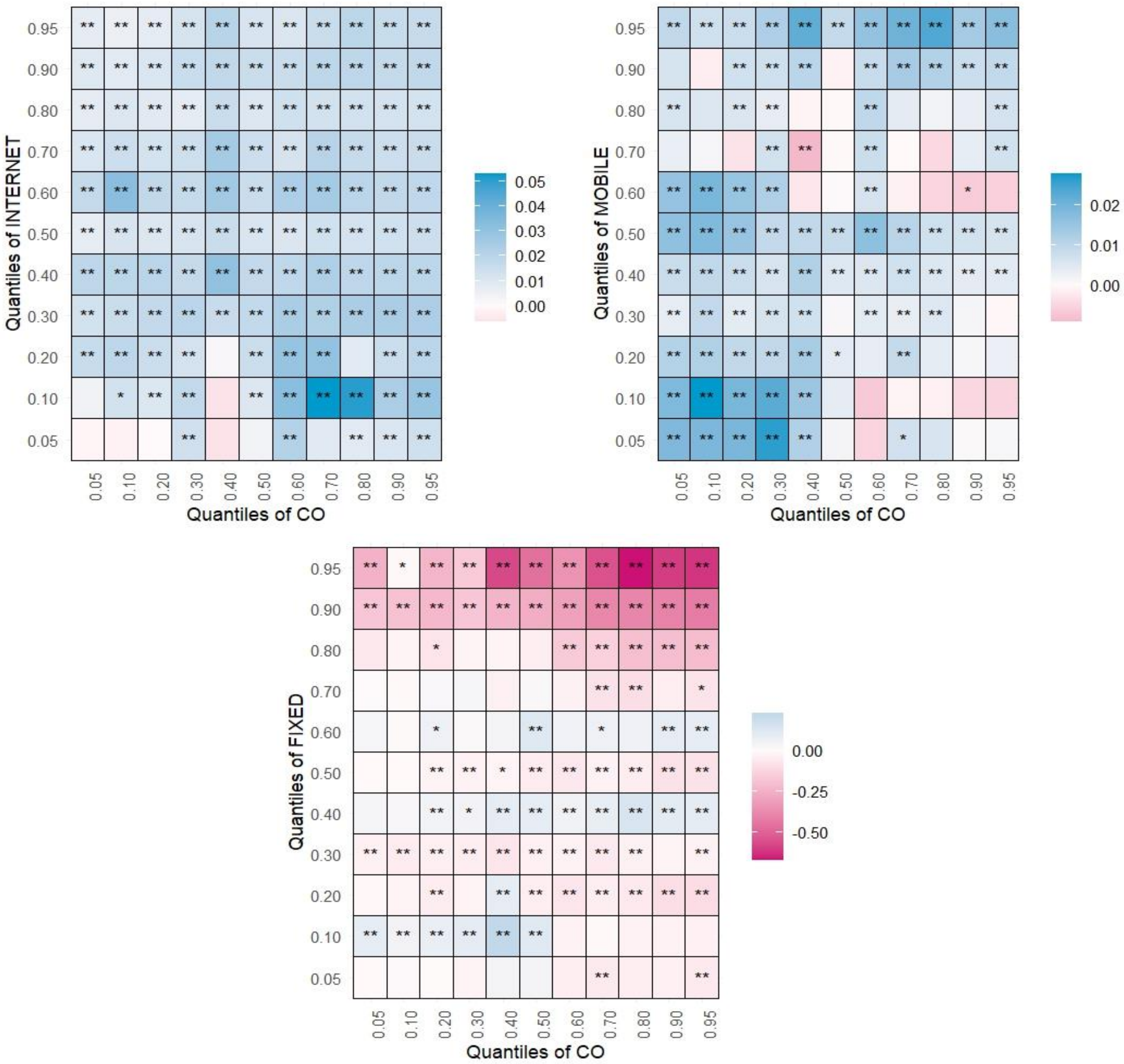


Figure 5. QQKRLS results

The QQKRLS results presented in Figure 5 show that the relationship between digitalization indicators and carbon emissions varies across quantiles. The findings regarding Internet usage indicate that positive and statistically significant coefficients dominate in most quantiles of CO. This result supports the positive directional effect observed in the CQR analysis and shows that the relationship remains stable across various quantile combinations. The results obtained for mobile usage also display positive and significant values across a wide range of quantiles. The fact that the mobile variable exhibits stronger coefficients particularly in the middle and upper quantile regions confirms the positive relationship identified in the CQR analysis. The QQKRLS findings demonstrate that the relationship between mobile usage and CO remains consistently positive across different emission levels. For fixed line usage, the coefficients are predominantly negative and significant in most quantiles. More pronounced negative values are observed in the lower and middle quantiles of CO, indicating that the mitigating effect seen in the CQR results is also supported by QQKRLS. The similar pattern of the fixed line variable across quantiles demonstrates the consistency of the relationship across methods.

Overall, the QQKRLS results support the main relationship patterns obtained through CQR; Internet and mobile indicators show a positive relationship in most quantiles, while the fixed line indicator predominantly exhibits a negative relationship. The method’s ability to illustrate the relationship across quantiles in detail strengthens the robustness of the findings.

5. Discussion

The main finding of this study is that different components of digitalization in Türkiye produce effects in different directions on environmental quality. While internet use and mobile subscriptions show a positive relationship with carbon emissions, fixed line usage is found to have an emission reducing effect. These results partially align with empirical studies emphasizing that digitalization does not automatically imply a "green" transformation and may create additional environmental pressure, particularly through the channels of rising energy demand and electricity consumption (Zhang and Wang 2023; Du and Wang 2024). On the other hand, studies showing that smart city applications and digital infrastructure investments can reduce carbon intensity indicate that digitalization can also have a mitigating potential depending on its design and institutional framework (Ma and Wu 2022; Yang et al. 2022). In this respect, the findings for Türkiye suggest that the direction and content of digitalization play a decisive role in shaping environmental outcomes.

The positive relationship found for internet usage should be interpreted alongside the dual sided discussion in the literature on the environmental impacts of internet technologies. Studies examining the global relationship between internet access and carbon emissions report that digital penetration can increase energy consumption while also enabling cleaner choices in the long run through channels such as human capital and environmental awareness (Wang and Xu 2021; Zhang et al. 2020). Other findings emphasize that the environmentally friendly use of internet based systems is shaped by users’ environmental sensitivities (Goethals and Ziegelmayer 2024; Xie 2024). The fact that internet use in this study worsens environmental quality particularly in certain quantiles indicates that Türkiye’s digital infrastructure and usage patterns still operate in ways that increase energy demand, and that environmental benefits have not yet been fully internalized. Compared with regional or city level studies showing that internet development can sometimes be associated with emission reduction (Pan et al. 2023), this suggests that country and period specific differences matter significantly.

It is also notable that the results for mobile subscriptions differ from many enterprise level digitalization findings in the literature. A wide range of studies at the firm or sector level report that digital transformation can reduce emission intensity through process optimization, resource efficiency, and the adoption of green technologies (An and Shi 2023; Shang et al. 2023; Li and Liao 2022; Fang et al. 2022; He et al. 2025; Ma et al. 2023; Zhang et al. 2023; Yao et al. 2024; Niu et al. 2025). The positive association between mobile usage and carbon emissions found in this study suggests that household and consumer driven digital expansion may leave a different environmental footprint from the efficiency gains observed at the enterprise level. The negative impact of fixed line usage on emissions, by contrast, is consistent with findings highlighting the link between digital infrastructure and energy efficiency, but it provides a more original and detailed contribution because most studies do not explicitly distinguish fixed lines (Adha et al. 2023; Onyeneke et al. 2024).

The quantile based results of this study methodologically complement the existing literature, which often focuses on average effects through panel or time series models. Studies examining the relationship between digitalization, energy, and environmental indicators typically analyze these links within a linear framework and report a single long run coefficient (Ullah et al. 2024; Yu and Liu 2024; Ni et al. 2022; Škare et al. 2024). While these findings reveal significant trends, they only partially reflect how the effects vary depending on emission levels. In this regard, the quantile based results obtained using Cross Quantile Regression, MQR, and QQKRLS demonstrate that the environmental effects of different types of digitalization intensify within specific emission regimes and exhibit nonlinear structures. This framework enables policymakers especially in countries like Türkiye, where the digital transformation process is ongoing to reconsider digital infrastructure investments and regulatory frameworks through an emission sensitive perspective that accounts for regime differences.

6. Conclusion and policy implications

This study examines the effects of different digitalization indicators on sustainable environmental management in Türkiye using quarterly data for the period 1993-2023 and quantile based econometric methods. The findings reveal that the digitalization-emissions relationship exhibits a nonlinear and quantile specific structure. Both the CQR and QQKRLS analyses show that increases in internet and mobile usage are associated with higher CO_2 emissions across most quantile ranges, whereas fixed line usage exerts a mitigating effect particularly at low and medium emission levels. These results indicate that the environmental outcomes of digital infrastructure differ according to the technological form and its energy consumption profile.

The findings suggest that the expansion of digitalization without attention to energy efficiency may increase carbon intensity. The stronger environmental pressure observed in higher emission quantiles for internet and mobile networks underscores the need to integrate digital infrastructure with renewable energy and to promote energy efficient network technologies. Given that rising mobile data usage elevates energy demand, it is important to encourage operators to adopt energy efficient 5G/6G technologies and to promote infrastructure sharing.

The negative association between fixed line usage and emissions at lower quantiles indicates that increasing fiber penetration may serve as an environmentally compatible policy tool. By balancing mobile data traffic and enhancing long term energy efficiency, fiber infrastructure emerges as a strategic factor in reducing the environmental costs of digitalization. Therefore, the digital transformation process should not rely solely on mobile centric structures; rather, a holistic approach that integrates fixed and mobile infrastructure is required.

The findings obtained for Türkiye indicate that the effects of different dimensions of digitalization on carbon emissions are not homogeneous and diverge depending on the type of digital infrastructure used. The positive relationship between internet usage and mobile communication indicators and CO_2 emissions suggests that digitalization in Türkiye primarily operates through consumption, service intensity, and energy demand increasing channels. Increased internet and mobile usage raise carbon emissions by expanding e-commerce volumes, increasing the energy demand of data centers, and accelerating electricity and fossil fuel consumption through the widespread use of digitally driven transportation and delivery activities. In contrast, the negative relationship between fixed line usage and CO_2 emissions can be explained by the fact that this infrastructure represents a relatively mature and more energy efficient communication technology. Compared to mobile networks, fixed line infrastructure has lower unit energy consumption, benefits from economies of scale in data transmission, and limits additional carbon intensive infrastructure investments. Moreover, the stronger association of fixed line usage with institutional, established, and planned communication structures may generate emission-reducing effects by enhancing digital efficiency and coordination in production processes. These findings demonstrate that the environmental impacts of digitalization in Türkiye are sensitive to the type of technology used and highlight the need for digital transformation policies to be designed in a way that promotes low-carbon digital infrastructures.

Overall, the results demonstrate that the environmental effects of digitalization are not homogeneous and vary across emission regimes. Thus, policy design should be based on a framework that accounts for quantile level heterogeneity, prioritizes energy efficiency, and differentiates technology types. Digital infrastructure investments supported by renewable energy, stronger carbon performance standards for digital service providers, digital carbon-monitoring systems in public institutions, and the widespread adoption of energy efficient devices constitute essential components of a sustainable digital transformation.

In sum, this study is one of the few analyses to evaluate the environmental effects of digitalization from a quantile based perspective and shows that managing the energy intensity of digital infrastructure is critical for Türkiye to achieve its sustainable development goals. The findings highlight the need for digital transformation policies to integrate environmental and technological dimensions simultaneously and provide policymakers with a quantile sensitive analytical foundation.

7. Limitations and directions for future research

This research contains certain limitations stemming from the scope of the analysis, the dataset used, and the methodological framework. The empirical examination relies exclusively on quarterly data for Türkiye; therefore, the findings are shaped by the country's unique economic structure, level of digitalization, and energy composition. As a result, the relationships identified may not be directly generalizable to countries with different institutional characteristics or digital transformation trajectories. Furthermore, the digitalization indicators used in the study are limited to the core variables available in the World Bank database, which prevents the inclusion of more detailed components of digital infrastructure such as cloud technologies, data centers, artificial intelligence based services, or 5G networks. This constraint implies that the environmental impacts of digitalization are assessed only through broad aggregate indicators.

Future research would benefit from expanding the analysis to include cross country comparisons, allowing a deeper understanding of how the environmental effects of digitalization differ depending on institutional quality, the share of renewable energy, energy efficiency policies, and economic development levels. The use of richer datasets capturing the micro components of digitalization for example data center energy use, the electricity demand of artificial intelligence applications, cloud infrastructure density, or the carbon footprint of 5G and 6G networks could significantly enhance the precision and depth of the results. Additionally, applying methodologies capable of evaluating causality such as quantile Granger causality, nonlinear ARDL, or wavelet quantile techniques would make it possible to examine the time varying and regime dependent structure of the digitalization environmental relationship within a more comprehensive analytical framework.

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.

Acknowledgments

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

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Journal of Sustainable Digital Futures 2025 1(2)

Journal of Sustainable Digital Futures

journal homepage: https://jsdf.org.tr/

Transforming towards sustainable digital futures: Global interactions between ESG and digitalisation indices

Nehir BALCI[1]

HIGHLIGHTS

[1] Dokuz Eylül University, Faculty of Business Administration, İzmir, Türkiye, nehir.balci@deu.edu.tr

ARTICLE INFO

Keywords:

Digitalization
ESG performance
Quantile-on-Quantile
Connectedness
Sustainability indices

ABSTRACT

This study investigates the global interconnectedness between digitalization and Environmental, Social, and Governance (ESG) performance using the Quantile-on-Quantile (QQ) Connectedness approach. The analysis employs the S&P 500 ESG Tilted Index, MSCI World ESG Leaders Index, and STOXX Global Digitalisation Index to evaluate the dynamic relationships between sustainability indices and market indicators of digitalization. The findings reveal strong and positive connectedness between digitalization and ESG indices, particularly at the lower and upper tails of the distribution. Moreover, sustainability indices generally act as dominant transmitters toward digital technology indices, whereas digitalization indices occasionally influence ESG indices during specific periods. These results indicate that sustainability-driven investment flows play a defining role in shaping the digital sector globally. The study contributes to the literature by providing a holistic and multidimensional assessment of the digitalization ESG nexus and offers strategic implications for investors, policymakers, and firms. Additionally, the findings highlight the critical importance of sustainable technology investments and digital transformation strategies for corporate performance.

1. Introduction

Digitalization has emerged as a key transformational force reshaping the Environmental, Social, and Governance (ESG) performance of firms. The literature provides strong evidence that digital technologies enhance sustainability practices at both the operational and corporate governance levels. The use of digital tools such as big data analytics, cloud computing, artificial intelligence, and automation enables firms to generate more accurate data, improve decision-making processes, and establish more robust sustainability strategies (Eriandani and Winarno 2023; Fang et al. 2023). This transformation not only optimizes processes but also improves governance quality and increases transparency toward stakeholders.

The impact of digitalization on environmental performance is particularly pronounced, offering significant gains in energy efficiency, emissions reduction, and optimized resource use. Artificial intelligence, IoT, and sensor systems reduce carbon footprints across production and logistics, while enhancing the monitoring, measurement, and reporting of environmental impacts (Zhou and Liu 2023; Lu et al. 2024). Digitalized supply chains further strengthen traceability, resulting in improvements in

Recieved 21 November 2025; Received in revised from 22 December 2025; Accepted 28 December 2025
Available online 30 December 2025

waste management, green procurement, and environmental risk mitigation (Tian et al. 2025; Chen et al. 2024a). Accordingly, digital transformation is closely aligned with environmental sustainability strategies. The effects of digitalization are also evident in the social and governance dimensions. In the social domain, digital tools offer firms significant advantages in enhancing worker safety, improving operational processes, protecting consumer rights, and safeguarding data privacy (Zhao et al. 2024; Wang and Esperança 2023). In governance, blockchain, automated auditing mechanisms, and digital reporting systems strengthen corporate transparency, enhance accountability, and reduce ethical risks (Moro-Visconti 2022; Agag et al. 2025). Thus, digitalization functions as a critical lever that enhances social responsibility and governance quality.

Finally, the literature emphasizes that digital transformation strengthens ESG performance not only directly but also indirectly through innovation capacity and dynamic capabilities. Digital tools enhance firms' ability to generate green innovation, establish sustainable supply chains, improve corporate risk management, and create long-term value (Su et al. 2023; Zhong et al. 2023). Several studies further show that firms with stronger ESG performance are more likely to adopt digital solutions and that the relationship between ESG and digitalization is mutually reinforcing (Zhao et al. 2023; Cheng and Li 2025). Taken together, these findings clearly demonstrate that digitalization represents a strategic and holistic transformation mechanism that enhances firms' ESG performance.

The strengthening of sustainability and ESG performance through digitalization can be explained indirectly, rather than directly, by the mechanisms proposed in Agency Theory and Dynamic Capabilities Theory, since the ESG concept did not exist when these theories were originally developed. Agency Theory argues that information asymmetry and monitoring problems between managers and owners can be reduced through technological tools (Jensen and Meckling 2019; Fama and Jensen 1983). Digital reporting, data transparency, and traceability systems enhance the monitoring of managerial behavior in line with the theory's predictions, thereby increasing accountability, which corresponds to the governance dimension of today's ESG framework.

On the other hand, Dynamic Capabilities Theory emphasizes that firms must develop agile, learning, and innovative capacities to remain competitive (Teece et al. 1997). Digital technologies provide firms with new capabilities in areas such as environmental efficiency, process optimization, supply chain traceability, and stakeholder engagement, indirectly supporting sustainable performance. Therefore, although ESG did not exist when these theories were formulated, the mechanisms they propose, such as transparency, monitoring, innovation, and adaptive capability, offer a strong theoretical foundation for explaining how digitalization enhances ESG performance today.

The primary objective of this study is to investigate the dynamic interdependence between sustainability indicators and digitalization financial markets at the global level. In this context, the study examines the connectedness structure among the S&P 500 ESG Tilted Index (SPXETUP) and the MSCI World ESG Leaders Index (MIWO00L2TNUS), which proxy ESG performance, and the STOXX Global Digitalisation USD Price Index (IXDIGITK), which represents the performance of digitalization sectors. Together, these indices offer an integrated framework for assessing the financial implications of sustainability investment strategies alongside the evolving market dynamics of the digital economy. To achieve this objective, the study adopts the Quantile-on-Quantile (QQ) Connectedness framework proposed by Gabauer and Stenfors (2024), which enables the examination of dependence structures across the entire conditional distribution rather than being restricted to average effects.

The Quantile-on-Quantile (QQ) Connectedness approach facilitates the identification of asymmetries, regime dependent interactions, and quantile spillover dynamics between sustainability and digitalization markets under varying market conditions. In particular, it captures how the magnitude and direction of connectedness evolve during tranquil periods as well as during episodes of heightened volatility and extreme market movements. By employing this advanced connectedness methodology, the study extends the existing literature by providing a more comprehensive depiction of market sensitivity and risk transmission mechanisms between sustainability and digital transformation indicators. Accordingly, the analysis contributes to a deeper understanding of how sustainability financial markets and digitalization sectors interact under different market regimes, thereby offering valuable insights into the structural linkages that shape global financial dynamics.

Although the existing literature provides extensive evidence on the effects of digitalization on firm level ESG performance, the interconnectedness between sustainability indicators and digitalization market indices at the global level remains largely unexplored. Prior studies predominantly rely on micro level firm data, leaving the macro-financial comovement between ESG and digitalization indices, the direction and intensity of shock transmission, and the underlying cross market dependency structure insufficiently examined. Consequently, the interaction between sustainability financial markets and digitalization market segments has not yet been systematically analyzed within a unified empirical framework.

In this context, the present study contributes to the literature by providing the first empirical investigation of the dynamic connectedness between global ESG market indices (SPXETUP and MIWO00L2TNUS) and a digitalization market index (IXDIGITK). Beyond its empirical scope, the study also advances the methodological frontier by employing the Quantile-on-Quantile (QQ) Connectedness approach proposed by Gabauer and Stenfors (2024). Unlike conventional connectedness frameworks that focus on average relationships, this approach enables the examination of dependence structures across the entire conditional distribution, thereby capturing asymmetries, regime dependent interactions, and quantile specific spillover dynamics. In doing so, it allows for a clear distinction between connectedness patterns prevailing during tranquil market conditions and those observed during periods of heightened volatility or market stress. By adopting this quantile connectedness perspective, the study offers a more comprehensive depiction of cross market dynamics between sustainability and digital financial markets, contributing both theoretically and methodologically to the existing literature.

From a practical standpoint, the findings carry important implications for multiple stakeholders. For investors, identifying the direction and intensity of shock spillovers between sustainability indices and digitalization indices is essential for effective portfolio diversification, risk management, and asset allocation strategies. For policymakers, understanding how digital transformation interacts with sustainability-oriented financial structures provides valuable insights for the formulation of green finance policies and digital economy regulations. For firms, insights into the degree of synchronization between digitalization-driven sectoral movements and ESG market performance offer strategic guidance for aligning sustainability initiatives with digital transformation processes. Accordingly, the study not only addresses a significant gap in the literature but also enhances the understanding of market dynamics at the intersection of sustainable finance and the digital economy.

This study consists of five sections. In the second section, the existing research on the relationship between digitalization and ESG is comprehensively summarized. In the third section, the dataset used in the study and the methodology based on the QQ Connectedness approach are introduced in detail. In the fourth section, the dynamic interaction between ESG indices and the digitalisation-themed index is analysed using the QQ Connectedness method. In the final section, conclusions are drawn based on the findings, and several recommendations are developed for investors, policymakers, and market participants.

2. Digitalization and ESG

The literature on the relationship between digitalization/digital transformation and ESG performance is grounded in the assumption that digital technologies can generate ESG outcomes by rendering firm level processes data driven, thereby enabling the measurement and reduction of environmental impacts, enhancing the traceability of social practices, and increasing the transparency of governance mechanisms. Within this framework, digitalization contributes to ESG performance through channels such as improving resource efficiency, optimizing processes to reduce emissions and waste, enhancing reporting quality, and strengthening accountability toward stakeholders (Zhou and Liu 2023; Su et al. 2023; Lu et al. 2024; Li et al. 2024; Yang et al. 2024; Liu et al. 2024). The ESG value creation of digitalization is also discussed through its role in firm valuation and the market value of digital intangible assets (e.g., data, software, and platform ecosystems), with the argument that ESG strategies, when combined with digital transformation, can generate stronger outcomes through valuation channels (Moro-Visconti 2022).

A substantial share of empirical findings converges on the conclusion that digital transformation enhances ESG performance. Increases in firms' levels of digitalization have been shown to improve ESG scores, a result that has been repeatedly documented using different datasets and model specifications, particularly within the Chinese context (Fang et al. 2023; Zhao and Cai 2023; Zhong et al. 2023; Wang et al. 2023a; Wang and Esperança 2023; Lu et al. 2024; Li et al. 2024; Zheng and Bu

2024; Liu et al. 2024). This stream of research argues that digitalization strengthens ESG performance not only through environmental channels but also by enhancing occupational health and safety, employee welfare, and the monitoring of supplier standards in the social dimension, as well as by improving internal control, risk management, and reporting quality in the governance dimension (Eriandani and Winarno 2023; Zhao et al. 2024; Peng et al. 2023). In this context, digitalization has been conceptualized in some studies as a transformational capability that "unlocks sustainable value", suggesting that digital transformation, when combined with corporate strategy and implementation frameworks, systematically enhances ESG performance (Kwilinski et al. 2023).

Mechanism studies emphasize intermediate channels to explain the digital transformation and ESG relationship. The dynamic capabilities perspective demonstrates that digital transformation indirectly improves ESG performance by enhancing organizational learning, reconfiguration, and agility capacities required for adapting to environmental and social objectives (Su et al. 2023). The mediating role of green innovation further indicates that digital transformation strategies stimulate environmentally friendly product and process innovations, which subsequently translate into improved ESG outcomes (Zhao et al. 2023). In manufacturing contexts, innovation capabilities and servitization have been shown to jointly drive ESG performance, with digital transformation reinforcing these components and thereby contributing to sustainability outcomes (Chen and Wang 2024). In parallel, the complementary relationship between digital leadership and ESG management highlights the managerial capacity dimension of digital transformation by linking it to organizational innovation and sustainability outcomes (Niu et al. 2022).

The literature also differentiates the digitalization and ESG nexus across sectors. In the energy and utilities sectors, digitalization and ESG have been found to jointly influence financial performance, with sectoral characteristics such as capital intensity, regulatory pressure, and carbon costs strengthening this relationship (Morea et al. 2025). In manufacturing industries, digital transformation enhances ESG responsibility performance, and the digitally empowered ESG approach has been discussed using concepts such as "DESG" (Wang et al. 2023; Wang et al. 2023a). In the logistics sector, digitalization is argued to play a performance-enhancing role for ESG through competitiveness, operational efficiency, and stakeholder trust (Fan et al. 2025). Evidence from high stakeholder intensive fields such as healthcare further suggests that ESG and digital transformation can be jointly leveraged to build sustainable models (Sepetis et al. 2024). Findings from the telecommunications sector complement these sector explanations by demonstrating that digitalization supports ESG transformation (Vetrova et al. 2022).

Supply chain digitalization constitutes a rapidly expanding substream of the literature. Empirical evidence across different countries and samples shows that supply chain digitalization improves corporate ESG performance through enhanced traceability, data integrity, coordination, and risk management (Chen et al. 2024a; Tian et al. 2025). In this context, supply chain resilience emerges as a key mediating mechanism, as digital transformation strengthens firms' ability to withstand supply shocks and operational vulnerabilities, leading to improvements in ESG performance (Zhang and Huang 2024). Policy designs indicate that institutional frameworks such as supply chain innovation initiatives and digitalization pilot programs can influence ESG outcomes through supply chain digitalization (Zhu and Zhang 2024). Particularly in emerging economies, the decarbonization of supply chains requires multi level analyses of the interaction between regulation, digitalization, and ESG (Okeke 2025). Broader conceptual discussions, such as "ESG 2.0", further suggest that digitalization can evolve into a platform that scales sustainability outcomes (Zimin et al. 2024).

Financial channels are also prominent in the digitalization and ESG literature. Studies on digital finance and corporate ESG show that improved access to finance, enhanced transparency, and reduced monitoring costs can lead to better ESG performance (Mu et al. 2023). Evidence that digital transformation jointly affects market performance and ESG performance supports the view that digitalization represents a "dual-output" strategic capability (Wang and Esperança 2023; Zheng and Bu 2024; Farinha and de Fátima Pina 2025; de bem Machado et al. 2025; Li et al. 2025). From a productivity perspective, the relationship between digitalization, ESG performance, and total factor productivity underscores the complementarity between sustainability and efficiency (Geng et al. 2025). Findings on digital trade further indicate that transparency, innovation, and internationalization channels associated with digitalization can enhance ESG performance by strengthening market integration and openness (Li et al. 2025a).

The literature does not confine the direction of the relationship to a unidirectional framework. Evidence that ESG ratings can stimulate digital technology innovation suggests that ESG may act as a determinant of digital transformation (Hao et al. 2025). Similarly, studies reporting that ESG performance influences corporate digital transformation indicate that causality may also operate in the reverse direction (Cheng and Li 2025). These findings imply the presence of simultaneity and feedback mechanisms within the digitalization-ESG nexus and call for more robust empirical identification strategies.

Institutional regulations and governance behaviors further highlight the conditional nature of the digital transformation and ESG relationship. Quasi natural experiment designs based on environmental regulations and institutional frameworks examine the ESG effects of digital transformation using more causal approaches (Chen et al. 2024). The joint consideration of digital transformation and governance practices such as earnings management reveals that ESG performance interacts with reporting incentives and managerial behaviors (Wang and Hou 2024). The linkage between regional digitalization levels and firm ESG performance underscores the critical role of digital infrastructure and regional technology ecosystems in shaping corporate ESG outcomes (Li and Zhu 2024). Moreover, from a resource efficiency perspective, digitalization plays a macro-level role in improving alignment with ESG objectives by enhancing the efficiency of resource utilization within the digital economy (Zhou and Liu 2023).

The literature also emphasizes that the relationship between digitalization and ESG may vary according to different configurations of corporate digital technology sets. It is argued that heterogeneous combinations of applied digital technologies and implementation scenarios can generate differentiated ESG outcomes (Chen et al. 2025). From an organizational perspective, digitization paths are considered decisive in improving ESG performance, highlighting that digital transformation is not merely a technological investment but also an issue of organizational design and process standardization (Zhao et al. 2024). Studies employing artificial intelligence, particularly interpretable large language model approaches, suggest new methodological opportunities for measuring and explaining the digitalization–ESG relationship by jointly evaluating digitalization outcomes and ESG strategies (Kou et al. 2025). In the context of corporate decarbonization, digital transformation and ESG are also argued to create synergies that strengthen emissions reduction performance (Sun et al. 2025).

Bibliometric and systematic review studies indicate that research on digitalization and ESG has expanded rapidly and diversified thematically, especially after 2023. Bibliometric analyses at the ESG and digitalization intersection report that dominant themes include supply chain digitalization, innovation, sectoral applications, governance quality (Tan et al. 2025; Kozar and Bolimowski 2025). Systematic reviews examining the contribution of digital ESG to the Sustainable Development Goals integrate digital transformation with resilience and sustainable development objectives at both institutional and policy levels (Kumar and Shah 2025). Evidence from different business contexts further confirms that the potential of digitalization to enhance ESG performance is conditioned by sectoral and organizational characteristics (Agag et al. 2025). A recent integrative review also synthesizes contemporary developments, case evidence, and relational patterns related to improving ESG performance through digital transformation, highlighting the maturation of this research field (Yu et al. 2026).

Overall, the literature consistently demonstrates that digitalization generates significant improvements in ESG performance across environmental, social, and governance dimensions. Digital technologies support eco efficiency, reduce waste, enhance social well-being, and increase corporate accountability through improved data management and decision-making processes. In sum, the integration of digital transformation into corporate sustainability strategies serves as a powerful mechanism for achieving long term value creation and responsible business conduct across industries.

3. Data and methodology

3.1. Data

The study examines the connectivity of the S&P 500 ESG Tilted Index (SPXETUP), the MSCI World ESG Leaders Index (MIWO00L2TNUS), and the STOXX Global Digitalisation USD Price Index (IXDIGITK). In other words, the study aims to measure the interaction between indices based on ESG performance and digitalization financial market indicators on a global scale. The S&P 500 ESG Tilted Index, the MSCI World ESG Leaders Index, and the STOXX Global Digitalisation USD Price Index are three important indicators used to measure the dynamics of sustainability and digital transformation in global financial markets. SPXETUP provides a sustainability view of the U.S. market by reweighting companies in the S&P 500 based on ESG criteria. The MSCI World ESG Leaders Index covers a broad pool of companies from both developed and emerging countries and includes firms that demonstrate strong ESG performance on a global scale. In contrast, IXDIGITK tracks the stock performance of companies operating in digitalisation sectors, reflecting market movements associated with the digital economy. When evaluated together, these three indices allow for a comprehensive analysis of the interaction between sustainability and digital transformation, cross sectoral interconnectedness, and market sensitivity.

The daily data are collected from Refinitiv between April 6, 2020, and November 6, 2025, and the study period depends on data availability. The data series is transformed into a return series $[Ln(P_t - P_{t-1}) \times 100]$ to satisfy the stationarity requirement imposed by the Quantile-on-Quantile (QQ) approach methodology. The return series is demonstrated in Figure 1, and descriptive statistics of the return series are reported in Table 1. Figure 1 illustrates that from 2020 to 2025, the three indices display generally stable return behaviour, but a significant market shock occurs in early 2025. The S&P 500 ESG Tilted Index (SPXETUP) and the MSCI World ESG Leaders Index (MIWO00L2TNUS) exhibit similar behaviour, reflecting their common ESG focus, while the STOXX Global Digitalisation USD Price Index (IXDIGITK) demonstrates higher volatility and return potential. ESG investments react less frequently but more intensely to systemic events, while digital technology exhibits more frequent reaction.

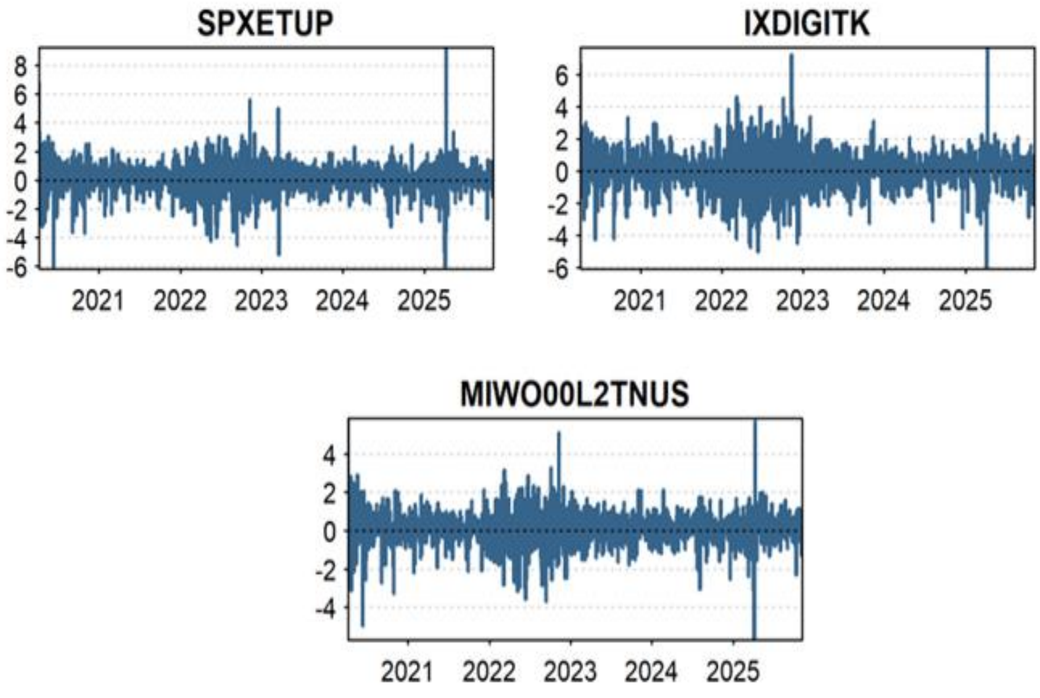

Figure 1. Return series of ESG and digitalisation indices

Table 1 shows that all mean values of indices are positive and above zero. The S&P 500 ESG Tilted Index (SPXETUP) has the highest mean value (0.074) and the second highest volatility (sd = 1.167), which shows the index's growth potential and uncertainty risk. The MSCI World ESG Leaders Index (MIWO00L2TNUS) has the second highest mean value (0.068) and the third highest volatility (sd = 0. 972). The negative skewness of all indices indicates vulnerability to external shocks and downturns, and the high kurtosis values above three suggest the potential for extreme price movements. Moreover, the null hypothesis of the Jarque-Bera test (1980) null is rejected for all indices, highlighting that the indices are not normally distributed, and the unit root tests confirm that the indices are stationary. The correlation matrix indicates a positive relationship between all indices.

Table 1. Descriptive statistics

	SPXETUP	**MIWO00L2TNUS**	**IXDIGITK**
Mean	0.074	0.068	0.053
Median	0.102	0.086	0.120
Maximum	9.253	5.842	7.669
Minimum	-6.189	-5.690	-6.082
Std. Dev.	1.167	0.972	1.327
Skewness	-0.055	-0.129	-0.058
Kurtosis	8.912	6.958	5.714
Jarque-Bera	2030.890	913.594	428.473
Probability	0.000	0.000	0.000
Unit Root Tests			
ADF	-39.618***	-34.293**	-33.020***
	0.000	0.000	0.000
Philips-Perron	-40.247***	-34.211**	-32.875***
	0.000	0.000	0.000
Correlation Matrix			
SPXETUP	1.000		
MIWO00L2TNUS	0.932	1.000	
IXDIGITK	0.835	0.881	1.000

Note: *** symbolizes significance at the 1% level.

3.2. Methodology

The study employed the QQ approach developed by Gabauer and Stenfors (2024) to investigate the relationship between the digitalisation index and the ESG market indices. Building upon the quantile connectedness approaches of Chatziantoniou et al. (2021) and Ando et al. (2022), this approach generalizes their methods through the integration of variable cross quantile interdependencies. As a first step in applying the methodology, quantile-level dependencies are obtained using the Quantile Vector Autoregressive model of order p, QVAR(p) formulated in Equation (1).

$$x_t = \mu(\tau) + \sum_{j=1}^{p} B_j(\tau)\, x_{t-j} + u_t(\tau) \tag{1}$$

In this specification, x_t and x_{t-j} represent K-dimensional vectors of endogenous variables, with τ capturing the quantile range [0, 1] and p denoting the order of lags used in the QVAR framework. Here, $\mu(\tau)$ refers to the K×1 conditional mean vector, $B_j(\tau)$ to the K×K coefficient matrix, and $u_t(\tau)$ to the K×1 error vector with a corresponding K×K variance-covariance matrix. As a subsequent step, the QVAR model is converted into a Quantile Vector Moving Average (QVMA) form using the Generalized Forecast Error Variance Decomposition (GFEVD) technique of Koop et al. (1996), developed by Gabauer and Stenfors (2024). According to Wold's Decomposition Theorem, the QVAR process can be represented as a moving average of past shocks, as shown in Equation (2):

$$x_t = \mu(\tau) + \sum_{j=1}^{p} B_j(\tau) x_{t-j} + u_t(\tau) = \mu(\tau) + \sum_{i=0}^{\infty} A_j(\tau)\, u_{t-1}(\tau) \quad (2)$$

The formulation in Equation (2) demonstrates the effect of shocks originating from j on the dynamics of i across an F-step horizon. In this context, is specified as a K×1 unit vector with one in the ith element and zeros elsewhere. The formulation in Equation (3) demonstrates the effect of shocks originating from j on the dynamics of i across an F-step horizon. In this context, e_i is specified as a K×1 unit vector with one in the ith element and zeros elsewhere. The transmission of a disturbance originating in series j to series i is assessed using the F-step-ahead GFEVD, as formalized in Equation (3).

$$\varphi^{g}_{i\leftarrow j,\tau}(F) = \frac{\sum_{f=0}^{F-1}\left(e_i' A_f(\tau) H(\tau) e_j\right)^2}{H_{ii}(\tau)\sum_{f=0}^{F-1}\left(e_i' A_f(\tau) H(\tau) A_f(\tau)' e_i\right)}, gSOT_{i\leftarrow j,\tau}(F) = \frac{\varphi^{g}_{i\leftarrow j,\tau}(F)}{\sum_{j=1}^{k}\varphi^{g}_{i\leftarrow j,\tau}(F)} \quad (3)$$

Following Diebold and Yilmaz (2012), the connectedness measure $\varphi^{gen}_{i\leftarrow j,\tau}(H)$, is scaled by the total of its corresponding row to $gSOT_{i\leftarrow j,\tau}(F)$, which underpins the directional TO/FROM connectedness metrics. The FROM index captures the incoming connectedness to series i, whereas the TO index measures its outgoing influence on the remaining variables, as formalized in Equations (4) and Equation (5).

$$S^{gen,to}_{i\to\bullet,\tau} = \sum_{k=1,i\neq j}^{K} gSOT_{k\leftarrow i,\tau} \quad (4)$$

$$S^{gen,from}_{i\leftarrow\bullet,\tau} = \sum_{k=1,i\neq j}^{K} gSOT_{i\leftarrow k,\tau} \quad (5)$$

The net aggregate directional connectedness, as expressed in Equation (6), is obtained by subtracting the FROM measure from the TO measure for a given series.

$$S^{gen,net}_{i,\tau} = S^{gen,to}_{i\to\bullet,\tau} - S^{gen,from}_{i\leftarrow\bullet,\tau} \quad (6)$$

The condition $S^{gen,net}_{i,\tau} > 0$ designates series i as a net shock transmitter, while $S^{gen,net}_{i,\tau} < 0$ categorizes it as a net shock receiver. Finally, the adjusted TCI, bounded between 0 and 1 and developed by Chatziantoniou et al. (2021), is calculated using Equation (7).

$$TCI_\tau(F) = \frac{K}{K-1}\sum_{k=1}^{K} S^{gen,from}_{i\leftarrow\bullet,\tau} \equiv \sum_{k=1}^{K} S^{gen,to}_{i\to\bullet,\tau} \quad (7)$$

4. Empirical results

The study employed 60-month rolling window quantile autocorrelation (QVAR) models with a six-step forecasting horizon for both the ESG index and the digitalization index to examine the interconnection between them. The average dynamic connectedness results for the S&P 500 ESG Tilted Index (SPXETUP) and STOXX Global Digitalisation USD Price Index (IXDIGITK) pair are demonstrated in Figure 2. The average dynamic connectedness quantiles range from 0.05 to 0.95 with intervals of 0.225 between consecutive quantiles. The intensity of blue coloration corresponds to the degree of interconnectedness, with darker tones signifying robust connections and lighter tones, fading to white, indicating minimal linkage.

The results display that the peak average total connectedness (94%) for the S&P 500 ESG Tilted Index (SPXETUP) and STOXX Global Digitalisation USD Price Index (IXDIGITK), observed at a point in the distribution where the relationship is directly related quantiles, τ_1 = 0.05, τ_2 = 0.05.

Moreover, the total connectedness results are likewise observed to peak at the same quantile for remaining quantiles. For instance, the average total connectedness is 93.7% for the S&P 500 ESG Tilted Index (SPXETUP) and the STOXX Global Digitalisation USD Price Index (IXDIGITK) index at the 95th quartiles. The total connectedness indices are generally higher at the directly related extreme quantiles (i.e., [τ_1 = 0.95, τ_2 = 0.95] and [τ_1 = 0.05, τ_2 = 0.05], representing the southwest and northeast corners) than at the reversely related extremes ([τ_1 = 0.95, τ_2 = 0.05] and [τ_1 = 0.05, τ_2 = 0.95], corresponding to the northwest and southeast corners).

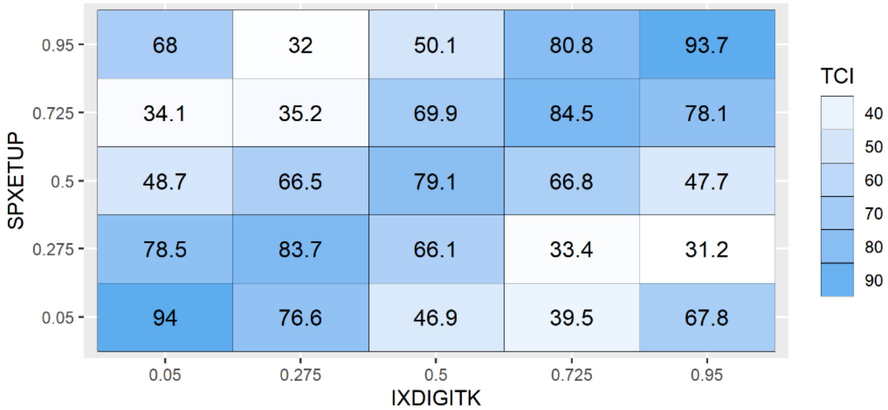

Figure 2. Quantile total connectedness indices for SPXETUP and IXDIGITK

The average dynamic connectedness results for the MSCI World ESG Leaders index (MIWO00L2TNUS) and the STOXX Global Digitalisation USD Price Index (IXDIGITK) pair are displayed in Figure 3. The results demonstrate that the peak average total connectedness (95.6%) for the MSCI World ESG Leaders index (MIWO00L2TNUS) and STOXX Global Digitalisation USD Price Index (IXDIGITK), observed at a point in the distribution where the relationship is directly related to quantiles, τ_1= 0.05, τ_2= 0.05. Moreover, the total connectedness results are likewise observed to peak at the same quantile for remaining quantiles. For example, the average total connectedness is 94.9% for the MSCI World ESG Leaders index (MIWO00L2TNUS) and the STOXX Global Digitalisation USD Price Index (IXDIGITK) index at the 95th quartiles. The total connectedness indices are generally higher at the directly related extreme quantiles (i.e., [τ_1 = 0.95, τ_2 = 0.95] and [τ_1 = 0.05, τ_2 = 0.05], representing the southwest and northeast corners) than at the reversely related extremes ([τ_1 = 0.95, τ_2 = 0.05] and [τ_1 = 0.05, τ_2 = 0.95], corresponding to the northwest and southeast corners).

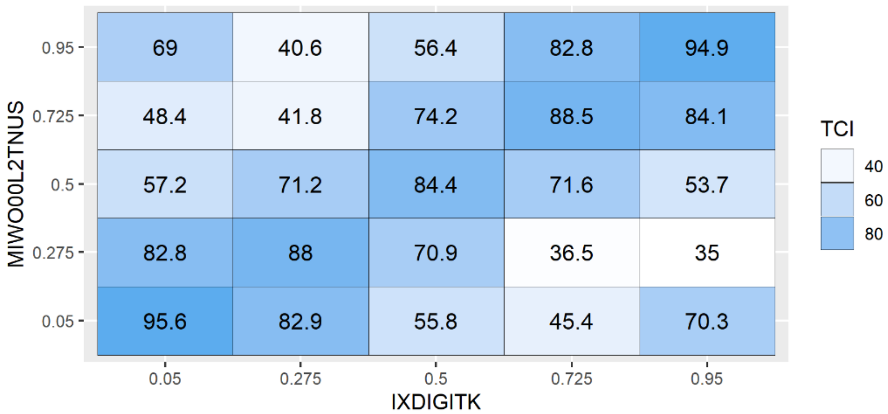

Figure 3. Quantile total connectedness indices for SPXETUP and MIWO00L2TNUS

Figure 4 plots the dynamic total connectedness indices (direct and inverse) and their differences (ΔTCI) to capture temporal patterns of parallel and counter directional interconnectedness for the S&P

500 ESG Tilted index (SPXETUP) and the STOXX Global Digitalisation USD Price index (IXDIGITK). The results display that direct TCI exceeds reverse TCI, indicating a strong positive linkage between the series.

The consistently negative ΔTCI values throughout the sample period indicate a strong unidirectional influence from the S&P 500 ESG Tilted index (SPXETUP) to the STOXX Global Digitalisation USD Price index (IXDIGITK). The dominance of the direct TCI suggests that the dynamics of the sustainability sector have a significant impact on the digital technology sector. The lack of reverse dominance suggests that developments in the digital sector do not significantly impact the sustainability index during this time frame. This likely reflects how sustainability mandates, green capital flows, and investor screening practices affect the tech-heavy index, rather than vice versa.

Figure 4. Direct and reverse total connectedness indices for SPXETUP and IXDIGITK

Figure 5 displays the dynamic total connectedness indices (direct and inverse) and their differences (ΔTCI) to capture temporal patterns of parallel and counter directional interconnectedness for the MSCI World ESG Leaders index (MIWO00L2TNUS) and the STOXX Global Digitalisation USD Price index (IXDIGITK). The results indicate that direct TCI exceeds reverse TCI, suggesting a strong positive correlation between the series.

The persistent dominance of the direct TCI from MSCI World ESG Leaders Index (MIWO00L2TNUS) to the digital technology sector suggests a strong transmission channel driven by global sustainability trends. Negative ΔTCI values indicate that ESG market dynamics have a greater influence on digital technology firms than vice versa. This asymmetric impact may stem from increased regulatory, investment, and reputational pressures on tech firms to comply with ESG standards, while innovations in the tech sector have not yet significantly reshaped the overall composition of the ESG index.

Figure 5. Direct and reverse total connectedness indices for SPXETUP and MIWO00L2TNUS

Lastly, the study examines net directional connectedness across quantiles, and Figure 6 presents the results of net directional connectedness between the S&P 500 ESG Tilted index (SPXETUP) and the STOXX Global Digitalisation USD Price index (IXDIGITK). A three-color scale is utilized in Figure 6, with blue indicating elevated positive values, white reflecting neutral or near zero values, and red signifying negative extremes. Within the quantiles, positive values are associated with the S&P 500 ESG Tilted index (SPXETUP), which functions as a net transmitter, while negative values correspond to the STOXX Global Digitalisation USD Price index (IXDIGITK), taking on that role.

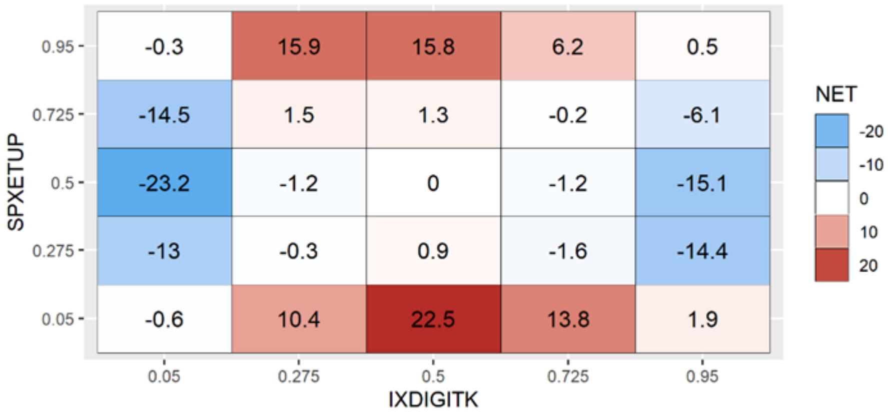

Figure 6. Net Quantile connectedness between SPXETUP and IXDIGITK

The quantile net TCI heatmap reveals an asymmetric information transmission structure between the ESG-tilted equity market and the digital technology sector. While the SPXETUP index acts as a net transmitter during periods of low ESG performance and mid level digital performance, it becomes a net receiver when the digital sector is in high or low extremes. The most substantial influence occurs when SPXETUP is at its weakest (τ = 0.05), highlighting the vulnerability of ESG indices to shocks originating in the technology sector. This supports the view that digital market dynamics exert nontrivial feedback effects on sustainability portfolios, particularly in volatile environments.

Figure 7 illustrates the results of net directional connectedness between the MSCI World ESG Leaders index (MIWO00L2TNUS) and the STOXX Global Digitalisation USD Price index (IXDIGITK). Figure 7 employs a three color gradient, where blue denotes high (positive) values, white represents values near zero, and red corresponds to low (negative) values. Within the quantiles, positive values are associated with the MSCI World ESG Leaders index (MIWO00L2TNUS), which acts as a net transmitter, while negative values correspond to the STOXX Global Digitalisation USD Price index (IXDIGITK), assuming that role.

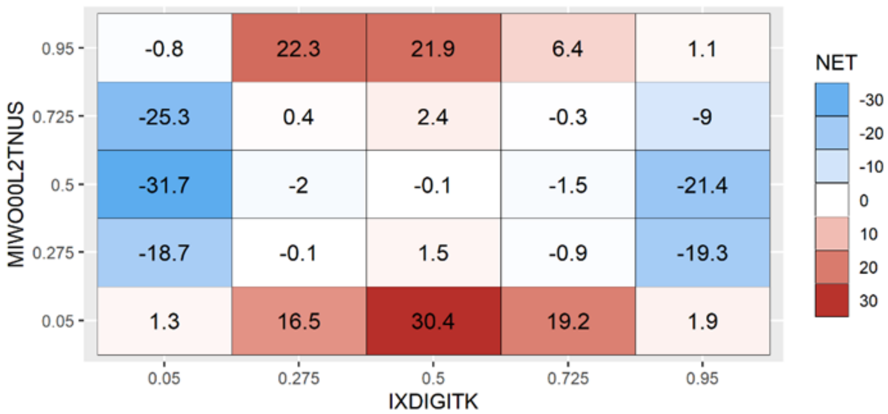

Figure 7. Net Quantile connectedness between MIWO00L2TNUS and IXDIGITK

The quantile spillover structure indicates an asymmetric dependence between the MSCI World ESG Leaders Index (MIWO00L2TNUS) and the digital technology sector. At lower ESG quantiles and moderate levels of digital index performance, the ESG index acts as a strong net transmitter. However, across most moderate to high quantiles of the ESG index, it becomes a significant net receiver, especially when the digital sector is in its tails. This implies that under normal or booming ESG conditions, the digital technology sector plays a more influential role in transmitting shocks or information to ESG-aligned assets.

5. Concluding remarks and policy suggestions

The findings of this study show that the relationship between sustainability and digitalization is strong but asymmetric, thereby supporting much of the current literature. Similar to many studies demonstrating that digital transformation improves ESG performance (Fang et al. 2023; Lu et al. 2024; Kwilinski et al. 2023), the results of this analysis confirm the presence of a highly dynamic interconnectedness between sustainability-themed indicators and digital technology markets. The observation that digitalization enhances corporate transparency, optimizes data processes, and supports technologies that reduce environmental impact (Zhou and Liu 2023; Su et al. 2023) aligns with the current study's finding of deep integration between these domains. Additionally, the evidence showing that the digital sector can dominate sustainability markets during volatile periods (Wang and Esperança 2023; Zhao et al. 2024) is clearly reflected in the current results. Conversely, in periods when sustainability-related policies and regulations strengthen, ESG indicators appear to exert a more influential role over the digital sector, which is consistent with studies emphasizing the market directing power of sustainability focused investor behavior (Agag et al. 2025; Morea et al. 2025). Thus, the findings demonstrate not only that the ESG-digitalization nexus is reciprocal, as indicated in the literature, but also that this relationship varies by context, period, and market conditions.

The results reveal that the interaction between sustainability and digitalization markets does not follow a stable structure but instead varies over time and is highly sensitive to market shocks. The fact that the digital sector becomes a dominant actor over sustainability assets during turbulent periods suggests that rapid innovation cycles, artificial intelligence applications, developments in data security, and platform-economy dynamics directly shape ESG related investment behavior. Conversely, in periods when environmental and social responsibility regulations strengthen, sustainability indicators appear to play a more guiding and stabilizing role over digitalization markets. This reciprocal yet asymmetric structure reflects investors' growing sensitivity to evolving sustainability norms, the increasing regulatory pressure faced by technology firms, and the rising degree to which green-transition expectations are priced into global markets. At the same time, the results indicate a mutual adjustment process: sustainability-linked assets increasingly benefit from digital innovation, while the digital sector simultaneously restructures itself in accordance with ESG principles and stakeholder expectations.

The findings of this study offer important strategic implications for policymakers, investors, and firms operating at the intersection of sustainability and digitalization. The strong interdependence observed between sustainability and digitalization markets indicates that regulatory frameworks would benefit from more explicitly embedding ESG principles within digital finance, data governance, and artificial intelligence–related activities. Integrating sustainability considerations into technology-oriented regulations may help mitigate sustainability related risks while enhancing transparency, particularly in sectors undergoing rapid digital transformation. From an investment perspective, the results suggest that portfolio construction and diversification strategies should extend beyond conventional ESG performance metrics to incorporate the cyclical behavior, volatility characteristics, and market influence of digitalization-oriented assets. As digital sector dynamics can exert a pronounced influence on sustainability focused portfolios during certain market conditions, explicitly accounting for these interactions within risk management and asset allocation frameworks may contribute to more resilient investment outcomes.

At the firm level, the evidence highlights the relevance of adopting an integrated strategic orientation that aligns sustainability objectives with digital transformation initiatives. In line with existing findings that digitalization can enhance ESG performance, firms may improve their sustainability outcomes by systematically deploying digital technologies in areas such as carbon-emissions monitoring, supply chain transparency, and resource efficiency management. Such integration enables more effective operationalization of sustainability goals while strengthening monitoring and reporting capabilities. The increasing prominence of sustainability norms within digitally intensive sectors further underscores the importance of robust ESG disclosure practices and sustainability innovation among technology firms. Regular reporting of environmental and social performance, together with investments in ESG's technological solutions, may enhance market credibility and support long term value creation. More broadly, these practices can facilitate the transition toward a digital economy that is increasingly aligned with sustainability principles.

This study examines the global digitalization and ESG connectedness based on three key indices (S&P 500 ESG Tilted Index, MSCI World ESG Leaders Index, and STOXX Global Digitalisation Index). However, since the analysis includes only these specific indices, it may not fully capture all digitalization dynamics or all components of ESG within the broader market. Future research may conduct a more detailed analysis of the relationship between digitalization strategies and ESG performance by employing more micro level datasets at the firm or sector level. In particular, studies measuring the effects of artificial intelligence investments, data analytics capacity, and sustainable technology applications on ESG scores would make a significant contribution to the literature. In addition, comparative analyses across different countries or regions can more clearly reveal the role of institutional structures, regulatory frameworks, and technological maturity levels in shaping connectedness.

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.

Acknowledgments

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

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Journal of Sustainable Digital Futures 2025 1(2)

Journal of Sustainable Digital Futures

journal homepage: https://jsdf.org.tr/

The impact of ICT, technological innovation, and digitalisation on achieving sustainable development goals in G20 economies

Havva KOÇ[1]

HIGHLIGHTS

[1] İstanbul Okan University, İstanbul, Türkiye, havva.koc@okan.edu.tr

ARTICLE INFO

Keywords:

Digital transformation
ICT exports
Technological innovation
Sustainable development
G20 countries

ABSTRACT

Digital transformation exhibits a dual nature: while it acts as a catalyst for sustainable development through innovation, efficiency, and inclusion, it simultaneously generates new risks such as energy intensity, inequality, and digital dependency. This study examines the long-run relationship between information and communication technologies (ICTs), digitalisation, technological innovation, and economic growth in the context of sustainable development for 14 G20 countries over the period 2000-2021. The analysis employs second-generation panel data techniques that account for cross-sectional dependence, heterogeneity, and structural breaks. The Durbin-Hausman and Westerlund-Edgerton cointegration tests confirm the existence of a long-term equilibrium relationship among the variables. Long-run coefficients are estimated by the Common Correlated Effects Mean Group (CCEMG) and Augmented Mean Group (AMG) models. The results indicate that digitalisation and economic growth have significant effects on sustainable development, whereas ICT exports and technological innovation display weaker linkages. The Dumitrescu-Hurlin panel causality test further reveals bidirectional causality between digitalisation and sustainable development, and unidirectional causality running from economic growth to sustainable development. Overall, the findings highlight the dual role of digital transformation as both a driver and a disruptor of sustainable development, emphasizing the need for balanced policy strategies that maximize digital benefits while minimizing sustainability risks assessment.

1. Introduction

Rapid advances in information and communication technologies have redefined the dynamics of economic growth and highlighted the digital dimension of sustainable development. Digitalisation creates potential for efficiency, innovation, and inclusiveness across a wide range of areas, from production processes to public administration. However, this transformation also brings challenges such as higher energy consumption, data-intensive production, income inequality, and the digital divide, all of which may hinder sustainable development. Therefore, digital transformation has a dual nature, acting both as a driver of sustainability and a source of new risks.

This dual structure makes it necessary to analyse the economic, environmental, and social dimensions of digitalisation in an integrated framework. On one hand, digital technologies improve resource efficiency and reduce environmental pressures. On the other hand, growing energy demand and

Received 20 November 2025; Received in revised from 17 December 2025; Accepted 28 December 2025
Available online 30 December 2025

electronic waste generation threaten environmental sustainability. Thus, the effect of digital transformation on sustainable development may differ depending on a country's technological capacity, energy infrastructure, and quality of institutional governance.

Recent research has shown that digitalisation positively influences economic performance, green innovation, and energy efficiency. Yet, these effects fluctuate over time due to structural breaks, policy changes, and technological inequalities. Hence, analysing the relationship between digital transformation and sustainable development requires methods that consider both long-term integration and cross-country heterogeneity.

This study investigates the effects of ICT service exports (LNICT), digitalisation (LNDIJIT), technological innovation (LNTECIN), and economic growth (LNGDP) on sustainable development (SDG) in 14 G20 countries from 2000 to 2021. Second-generation panel data techniques, which account for structural breaks and country-specific differences, are employed to examine the dual nature of digital transformation from a sustainability perspective.

The research problem stems from the limited empirical evidence on how digitalisation and ICT shape sustainable development both positively and negatively. There is a lack of comprehensive studies that explicitly account for structural breaks and national differences. This study seeks to answer the question: How do ICT, digitalisation, and economic growth influence sustainable development under structural breaks?

The main objective is to present a balanced view of the positive and negative impacts of digital transformation on sustainable development. Accordingly, the study aims to provide policy implications that enhance the benefits of digitalisation while mitigating its potential risks.

This research contributes to the literature by analysing the effects of digital transformation on sustainable development within the G20 context and under structural breaks. It jointly considers ICT, digitalisation, and technological innovation, offering a holistic perspective on the dynamics of sustainability. Moreover, it employs second-generation panel data methods (CIPS, Westerlund-Edgerton, CCEMG, and AMG) to statistically capture cross-country heterogeneity. In doing so, it provides an original methodological and conceptual contribution to the digitalisation-development nexus.

The remainder of the paper is structured as follows. Section 2 reviews the literature on the relationship between ICT, digitalisation, technological innovation, and sustainable development. Section 3 introduces the dataset, variables, and econometric methods used, followed by the empirical findings. Section 4 discusses the results in light of the existing literature. The final section presents the main conclusions and policy recommendations concerning the interaction between digital transformation and sustainable development.

2. Literature review

The rapid expansion of information and communication technologies (ICT) in the global economy has led to numerous studies exploring the interaction among economic growth, digitalization, and sustainable development. The literature has examined how digital transformation influences sustainability through production, trade, green innovation, and governance channels. In recent years, panel data-based research has quantitatively revealed the long-term effects of ICT on economic and environmental sustainability.

Evidence supporting the notion that sustainable development can be fostered through digitalization and economic growth channels has been growing steadily. Studies covering the European Union (EU) and OECD countries confirm that digital technologies enhance economic performance and improve sustainability indicators (Bocean and Vărzaru 2023; Fernández-Portillo et al. 2019; Gürler 2023; Herman 2022). Digital transformation has been shown to strengthen GDP growth and employment via e-commerce, ICT services, and high-tech sectors, thereby directly contributing to development by boosting productivity. Research on ASEAN countries demonstrates that digitalization accelerates growth through openness and education expenditures (Nurdiana et al. 2023), while in South Asia digital financial inclusion reduces poverty and supports inclusive growth (Safdar et al. 2024).

In a complementary line of inquiry, Cioacă et al. (2020) emphasize that digital transformation enhances competitiveness and sustainable development performance in EU economies by fostering technological adaptation and green innovation. Similarly, Antoniuk and Davydenko (2024) highlight that leveraging digital technologies enhances inclusive growth by improving citizens' access to quality services such as education and healthcare, thereby reinforcing the sustainable competitiveness of national economies.

Likewise, studies conducted in China confirm the positive effects of the digital economy on income levels and development quality. Within the framework of the "Broadband China" policy, the expansion of digital infrastructure has been found to raise income levels while deepening income inequality in favor of high-skilled labor (Kong et al. 2023). This suggests that while the digital economy strengthens growth, it may also produce heterogeneous social effects. Analyses on OECD countries show that ICT and financial access simultaneously feed the bright and dark sides of digitalization; while supporting growth through production and export channels, they also raise ethical and security issues (Alraja et al. 2023). At the same time, Ballı (2023) highlights the emerging challenges of digital transformation—such as unemployment, cybersecurity, and intellectual-property concerns—and proposes solutions to mitigate the social and economic risks accompanying the transition toward a digital economy.

The environmental and technological dimensions of digitalization have also been widely examined. Studies focusing on China and Belt-and-Road countries demonstrate that digital and technological progress has significant positive effects on sustainable growth and environmental performance (Zhao et al. 2022; Yang et al. 2022; Hao et al. 2023; Lei et al. 2024). Digitalization enhances energy efficiency, decarbonizes production processes, and strengthens green innovation capacity (Luo et al. 2023; Banelienė et al. 2023). In the EU context, empirical evidence further confirms that green innovation integrated with digital transformation fosters economic competitiveness and accelerates sustainable growth (Cioacă et al. 2020; Ahmed and Elfaki 2024).

Other studies point out that the environmental impact of digitalization differs depending on income level, energy structure, and technological intensity. Balsalobre-Lorente et al. (2025) report that ICT and green technologies improve environmental quality in advanced economies but remain limited in emerging ones, and that the positive effect of digitalization on green innovation is strengthened by institutional capacity and financial scale (He et al. 2024; Zhang and Bilawal Khaskheli 2025). In addition, Chen and Xing (2025) show that digital trade promotes inclusive and green growth by expanding markets, reducing pollution from conventional trade, and lowering entry barriers for small and medium-sized enterprises-highlighting digital trade as a key driver of socially inclusive sustainability.

A growing body of research emphasizes that ICT exports positively influence economic growth and development indicators across OECD and G20 countries (Gürler 2023; Bocean 2025). ICT exports increase value added by spreading knowledge-based services and enhancing competitiveness in the digital economy. Furthermore, digital service trade is reported to promote inclusive growth and improve SDG performance (Yeerken and Feng 2024; El Awady et al. 2025). Yet the environmental consequences of ICT exports remain underexplored, as most studies do not directly model the interaction between carbon emissions and sustainability objectives-revealing an open research gap on the long-term effects of digital openness on sustainable development.

The social dimensions of ICT and digitalization have also been investigated in terms of governance and inequality. Digital transformation has been found to enhance social inclusiveness and income equality, particularly by reducing gender disparities (Shah and Krishnan 2024). Similarly, when financial inclusion and governance quality are jointly assessed, digital services are observed to boost inclusive growth in disadvantaged regions (Safdar et al. 2024). However, some scholars argue that digitalization may intensify social polarization due to high skill requirements and regional inequalities (Kong et al. 2023). Therefore, ensuring that digital transformation supports sustainable development requires strengthening regulatory frameworks, reducing infrastructure disparities, and promoting digital skills and literacy (Zhang et al. 2025; Georgieva and Aleksandrova 2025).

This study addresses an important research gap and contributes to the existing literature. Although the existing studies have made significant contributions to understanding the nexus between digitalisation and sustainable development, several methodological and scope-related limitations remain. First, most of the literature relies on conventional panel models that ignore structural breaks, even though digital transformation has been strongly affected by events such as the 2001 crisis, the 2008 global recession, the 2015 technology wave, and the 2020 pandemic. Second, few studies examine the impact of ICT exports on sustainable development; most focus solely on internet usage or digital access indicators. Third, comprehensive studies that integrate developed and emerging G20 economies while accounting for cross-country heterogeneity are limited. Accordingly, this study provides three original contributions to the literature:

(i) It integrates ICT exports, digitalisation, technological innovation, and economic growth into a single framework to identify the multidimensional determinants of sustainable development.
(ii) It tests long-run cointegration relationships under structural breaks and cross-sectional heterogeneity using the Westerlund-Edgerton (2008) and Durbin-Hausman (2008) approaches.
(iii) It estimates robust long-run coefficients through CCEMG and AMG estimators and assesses bidirectional causal relationships using the Dumitrescu-Hurlin causality test.

Through these features, the study offers one of the first panel-level empirical evidences on the effects of the digitalisation-ICT export-growth nexus on sustainable development under structural breaks and heterogeneous country structures.

3. Data, methodology and finding

The analysis was conducted for 14 G20 countries using annual data covering the period 2000-2021. The variables and their sources are presented in Table 1.

Table 1. Definition and sources of variables

Variables	Description	Source / Indicator Code
SDG	SDG Index Score (excluding sub-components). Represents countries' performance toward achieving the Sustainable Development Goals.	United Nations Sustainable Development Solutions Network (SDSN)
LNICT	ICT service exports (BoP, current US$). Includes computer and communications services (telecommunications, postal, courier) and information services.	World Bank (WDI) *BX.GSR.CCIS.CD*
LNTECIN	Patent applications, nonresidents. Refers to worldwide patent applications filed by nonresidents through the PCT procedure or national offices.	World Bank (WDI) *IP.PAT.NRES*
LNDIJIT	Individuals using the Internet (% of population). Measures the percentage of people using the Internet via any device in the last three months.	World Bank (WDI) *IT.NET.USER.ZS*
LNGDP	GDP per capita (constant 2015 US$). Represents total income per person, adjusted for inflation to 2015 prices.	World Bank (WDI) *NY.GDP.PCAP.KD*

Note: All variables (except SDG) were transformed into their natural logarithmic form (LN) prior to estimation.

In the model, SDG was defined as the dependent variable, while LNICT, LNDIJIT, LNTECIN, and LNGDP served as explanatory variables. The basic panel regression model can be expressed as follows in Equation (1):

$$SDG_{it} = \alpha_i + \beta_1 LNICT_{it} + \beta_2 LNTECIN_{it} + \beta_3 LNDIJIT_{it} + \beta_4 LNGDP_{it} + \varepsilon_{it} \tag{1}$$

The descriptive statistics in Table 2 summarise the key properties of the variables used in the analysis. Each variable—SDG, LNDIJIT, LNTECIN, LNICT, and LNGDP—contains 294 observations. The mean value of SDG is 70.95, representing the widest range among the variables. Standard deviations vary between 1 and 8, indicating a moderate level of variability across the series. Skewness values show that SDG, LNDIJIT, and LNGDP are left-skewed, while LNTECIN and LNICT display more symmetric distributions. Kurtosis values hover around 3, except for LNDIJIT, which exhibits a leptokurtic distribution. The Jarque-Bera probabilities indicate that the normality assumption is rejected for most variables. To maintain a balanced panel structure, the following 14 countries were included in the analysis: Argentina (ARG), Brazil (BRA), Canada (CAN), China (CHN), France (FRA), Germany (DEU), India (IND), Japan (JPN), Mexico (MEX), Russia (RUS), South Africa (ZAF), South Korea (KOR), United Kingdom (GBR), and the United States (USA).

Table 2. Descriptive statistics

Stats	SDG	LNICT	LNTECIN	LNDIJIT	LNGDP
Mean	70.95080	22.13449	9.844611	3.662322	9.623483
Median	72.57642	22.25279	9.682614	4.121395	9.645209
Maximum	83.14347	25.32314	12.72588	4.569596	11.01942
Minimum	52.18668	17.37174	7.340836	-0.639546	6.628972
Std. Dev.	7.571910	1.687972	1.230361	1.030044	1.075594
Skewness	-0.650223	-0.191806	0.261850	-1.613994	-0.793580
Kurtosis	2.569842	2.095772	2.671898	5.156504	2.965381
Jarque-Bera	22.98341	11.81863	4.678441	184.6126	30.87340
Probability	0.000010	0.002714	0.096403	0.000000	0.000000
Sum	20859.53	6507.539	2894.316	1076.723	2829.304
Sum Sq. Dev.	16798.81	834.8299	443.5399	310.8701	338.9724
Observations	294	294	294	294	294

3.1. Cross-sectional dependence

In panel data models, the presence of common shocks may lead to cross-sectional dependence in the error terms. This problem can invalidate inferences based on the standard covariance matrix and reduce the efficiency of estimators. The Lagrange Multiplier (LM) test developed by Breusch and Pagan (1980) is widely used to examine the presence of correlation among cross-sectional units. The Cross-Section Dependence (CD) test proposed by Pesaran (2004) is applicable to both balanced and unbalanced panels. The later versions of this test—CDw and CDw+—introduced by Pesaran (2015) and Pesaran et al. (2008)—provide more reliable results, particularly for panels with large N and small T. Greene (2018) provides a detailed explanation of how the correlation coefficients of residuals are calculated in these tests. Under this section, the Breusch-Pagan Lagrange Multiplier Test and the Pesaran CD Test are introduced. The hypotheses for both tests are formulated as follows:

H_0: There is no cross-sectional correlation.

H_1: There is cross-sectional correlation.

Breusch and Pagan (1980) developed an LM-type test to detect the existence of correlation among cross-sectional units. The test can be applied to both balanced and unbalanced panels. The Breusch-Pagan test statistic is defined as Equation (2):

$$LM_\rho = \sum_{i=1}^{N-1} \sum_{j=i+1}^{N} T_{ij} \hat{\rho}_{ij}^2 \sim \chi^2_{N(N-1)/2} \tag{2}$$

In Equation (2), $T_{ij} = \min(T_i, T_j)$; in a balanced panel, $T_{ij} = T$. Here, $\hat{\rho}_{ij}$ denotes the correlation coefficient between the residuals of units i and j (Greene 2008). It is computed as Equation (3):

$$\hat{\rho}_{ij} = \frac{\sum_{t=1}^{T} \varepsilon_{it}\varepsilon_{jt}}{(\sum_{t=1}^{T} \varepsilon_{it}^2)^{1/2} (\sum_{t=1}^{T} \varepsilon_{jt}^2)^{1/2}} \tag{3}$$

The LM_ρ statistic follows an asymptotic chi-square distribution as $T \to \infty$ with N fixed. However, it is not suitable for large N panels. For this reason, a scaled version of the test statistic, shown in Equation (4), is used:

$$SCLM_\rho = \frac{1}{N(N-1)} \sum_{i=1}^{N-1} \sum_{j=i+1}^{N} \sqrt{T_{ij}} \hat{\rho}_{ij} \sim N(0,1) \tag{4}$$

Pesaran (2004) proposed the CD test to examine cross-sectional dependence in both balanced and unbalanced panels. Under the null hypothesis of no dependence, the CD statistic is asymptotically normally distributed. The test can be applied to both fixed- and random-effects models and is based on the average of pairwise correlation coefficients calculated from individual regression residuals. The Pesaran CD test statistic is given in Equation (5):

$$CD = \sqrt{\frac{2}{N(N-1)}} \sum_{i=1}^{N-1} \sum_{j=i+1}^{N} \sqrt{T_{ij}} \hat{\rho}_{ij} \sim N(0,1) \tag{5}$$

Monte Carlo simulations have shown that the Pesaran CD test performs well even when $N > T$.

Table 3. Cross-sectional dependence tests

Variables	CD	CDw	CDw+	BP LM
SDG	42.057 (0.000***)	124.480 (0.000***)	33.613 (0.000***)	1770.332 (0.000***)
LNICT	34.627 (0.000***)	90.147 (0.000***)	40.136 (0.000***)	1307.143 (0.000***)
LNTECIN	6.104 (0.000***)	56.368 (0.000***)	41.793 (0.000***)	851.452 (0.000***)
LNDIJIT	40.847 (0.000***)	117.395 (0.000***)	62.945 (0.000***)	1674.748 (0.000***)
LNGDP	36.939 (0.000***)	96.200 (0.000***)	74.008 (0.000***)	1388.807 (0.000***)

Note: CD, CDw, and CDw$^+$ tests were developed by Pesaran (2004), Pesaran (2015), and Pesaran et al. (2008), respectively. ***, **, and * indicate significance at the 1%, 5%, and 10% levels.

All *p*-values in Table 3 are statistically significant at the 1% level, indicating the existence of cross-sectional dependence among all variables in the panel. The probability values for all tests are below 0.05, confirming that cross-sectional dependence is present throughout the dataset.

3.2. Homogeneity test

In panel data analyses, the homogeneity test is applied to determine whether the parameters differ across countries or units. This test examines whether the slope coefficients are identical among cross-sectional units. The first study addressing this issue was conducted by Swamy (1970), who proposed the following statistic to measure the variation of slope coefficients across units, as shown in Equation (6):

$$\hat{S} = \sum_{i=1}^{N} (\hat{\beta}_i - \hat{\beta}_{WFE})' \frac{X_i' M_x X_i}{\hat{\sigma}_i^2} (\hat{\beta}_i - \hat{\beta}_{WFE}) \tag{6}$$

The approach of Swamy (1970) was later improved by Pesaran and Yamagata (2008) and introduced as the Delta (Δ) homogeneity test. According to this test, the following panel regression model is considered, as given in Equation (7):

$$Y_{it} = \alpha + \beta_i X_{it} + \varepsilon_{it} \tag{7}$$

In Equation (7), β_i represents the slope coefficient that may vary across individual units. Based on this model, Pesaran and Yamagata (2008) defined the hypotheses of the homogeneity test as follows:

$H_0: \beta_i = \beta$ Slope coefficients are homogeneous.

$H_1: \beta_i \neq \beta$ Slope coefficients are heterogeneous.

To test these hypotheses, Pesaran and Yamagata (2008) developed the following test statistics. For large samples, the test statistic is defined in Equation (8):

$$\widehat{\Delta} = \sqrt{N}\left(\frac{N^{-1}\hat{S} - k}{\sqrt{2k}}\right) \tag{8}$$

For small samples, the adjusted version of the statistic is expressed as Equation (9):

$$\widetilde{\Delta}_{adj} = \sqrt{N}\left(\frac{N^{-1}\hat{S} - k}{\sqrt{2k}}\right) \tag{9}$$

In Equation (9), N denotes the number of cross-sectional units, S represents the Swamy test statistic, and k is the number of explanatory variables. Under the null hypothesis H_0, the statistic follows an asymptotic standard normal distribution as $(N, T) \to \infty$ and $\sqrt{N/T} \to 0$. Pesaran and Yamagata (2008) note that this test provides reliable results in both large and small samples due to its asymptotic properties.

Table 4. Homogeneity test results

Test	**Δ**	**Δadj**
Pesaran-Yamagata (2008)	–4.914 0.000***	–6.500 0.000***

Note: ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

The test examines whether the effects of LNICT, LNTECIN, LNDIJIT, and LNGDP on SDG differ across countries. According to Table 4, the test statistics are significant at the 1% level ($p < 0.01$), indicating that slope coefficients vary among G20 countries. This result implies that the model parameters are heterogeneous across countries, reflecting differences in digitalisation, technology, ICT development, and economic size among the G20 economies.

3.3. CIPS panel unit root test

The CIPS (Cross-sectionally Augmented IPS) test developed by Pesaran (2007) is a second-generation unit root test that accounts for cross-sectional dependence in panel datasets. This method extends the standard IPS test (Im et al. 2003) by including the cross-sectional means of the dependent variable and its first difference in the ADF regression. By doing so, it controls for common shocks and unobserved factor structures across countries. The basic model of the CIPS test is specified in Equation (10) as follows:

$$\Delta y_{it} = a_i + b_i y_{i,t-1} + c_i \bar{y}_{t-1} + d_i \Delta \bar{y}_t + \varepsilon_{it} \tag{10}$$

In Equation (10), $\bar{y}_t = \frac{1}{N}\sum_{i=1}^{N} y_{it}$ represents the cross-sectional mean, Δ denotes the difference operator, and ε_{it} is the error term. The terms $\bar{y}_{t-1}$ and $\Delta\bar{y}_t$ control for the impact of common factors, such as global shocks or synchronized trends across countries. The hypotheses of the test are defined as:

$H_0: \beta_i = 0$ All series contain a unit root (non-stationary).

$H_1: \beta_i < 0$ At least one series is stationary.

For each cross-sectional unit, an individual CADF (Cross-sectionally Augmented Dickey–Fuller) statistic is estimated. The panel-level CIPS statistic is then obtained by averaging these individual CADF statistics, as shown in Equation (11):

$$CIPS = \frac{1}{N}\sum_{i=1}^{N} t_i^{CADF} \tag{11}$$

In Equation (11), t_i^{CADF} denotes the t-statistic derived from the individual ADF regression of unit i. Pesaran (2007) demonstrated through Monte Carlo simulations that the CIPS test provides robust and reliable results even in panels with small N and T. Therefore, the CIPS test is widely preferred for testing the stationarity of variables under the presence of cross-sectional dependence.

Table 5. Panel unit root test results

Variables	CIPS I(0)	CIPS I(1)
SDG	-1.981	-3.676***
LNICT	-2.029	-2.617***
LNTECIN	-1.934	-3.837***
LNDIJIT	-1.916	-3.604***
LNGDP	-1.609	-2.638***

Note: ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

As shown in Table 5, the results of the CIPS test indicate that all variables are integrated of order one, I(1). This finding suggests that the variables become stationary after first differencing, confirming their non-stationarity in levels.

3.4. Panel cointegration test with structural breaks

The Westerlund-Edgerton (2008) and Durbin-Hausman (2008) approaches propose a Lagrange Multiplier (LM) based method to test the existence of long-run cointegration relationships in panel data models.

This test belongs to the class of second-generation panel cointegration tests as it accounts for both cross-sectional dependence and possible serial correlation among series. In addition, it applies the bootstrap resampling technique to reduce bias and improve reliability in small samples. The basic model is expressed in Equation (12) as follows:

$$y_{it} = \alpha_i + x'_{it}\beta_i + z_{it}; \qquad z_{it} = u_{it} + \mu_{it}, \mu_{it} = \sum_{j=1}^{t} \eta_{ij} \tag{12}$$

In Equation (12), y_{it} denotes the dependent variable, x_{it} represents the explanatory variables, z_{it} is the error term, and μ_{it} stands for the stochastic trend component. The hypotheses of the test are defined as follows:

$$H_0: \sigma_i^2 = 0 \text{ Cointegration exists.}$$

$$H_1: \sigma_i^2 > 0 \text{ No cointegration exists.}$$

This approach is an extension of the LM-based panel cointegration test initially developed by McCoskey and Kao (1998). The Durbin-Hausman (2008) test examines the null hypothesis of cointegration and employs bootstrap critical values to obtain accurate results in small samples.

Westerlund and Edgerton (2008) further extended this framework by incorporating structural breaks and common factor dependence. The model allowing for breaks in both intercept and slope coefficients is given in Equation (13):

$$y_{it} = \alpha_i + \eta_i t + \delta_i D_{it} + x'_{it}\beta_i + (D_{it}x_{it})'\gamma_i + z_{it}; \qquad z_{it} = \lambda'_i F_t + v_{it} \tag{13}$$

In Equation (13), D_{it} represents the structural break dummy, F_t denotes common factors, and λ_i are factor loadings. The model thus allows for country-specific breakpoints that may occur at different times across cross-sections. The hypotheses of the Westerlund-Edgerton (2008) test are formulated as:

$$H_0: \phi_i = 0 \text{ No Cointegration.}$$

$$H_1: \phi_i < 0 \text{ Cointegration exists.}$$

The test statistics τ_n and ϕ_n follow a standard normal distribution, adjusted for structural breaks and common factors. Consequently, the test remains valid even when the timing of the breaks is unknown. The Westerlund-Edgerton (2008) approach improves upon the Westerlund (2005) test in two major respects:

(i) it does not require prior knowledge of break dates, and
(ii) its asymptotic distribution is independent of nuisance parameters, allowing for the use of fixed critical values.

Applying both tests together enables a comprehensive assessment of cointegration relationships under heterogeneity and structural breaks. While the Durbin-Hausman (2008) test investigates whether a homogeneous cointegration relationship exists across the panel, the Westerlund-Edgerton (2008) test evaluates whether this relationship persists in the presence of structural breaks.

Table 6. Panel cointegration test results

Durbin-Hausman (2008)	
dh_g	**dh_p**
1.808^{**}	-2.272
(0,035)	(0.988)
Westerlund-Edgerton (2008) with Structural Breaks	
τ_n	**φ_n**
-2.992^{***}	-3.349^{***}
0.001	0.000

Note: ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

As shown in Table 6, the group mean statistic of the Durbin-Hausman (2008) test (dh_g= 1.808; p = 0.035) is significant at the 5% level, whereas the pooled statistic (dh_p= –2.272; p = 0.988) is not. This implies that a homogeneous cointegration relationship does not hold across the entire panel, but heterogeneous cointegration relationships may exist in some countries. For the Westerlund-Edgerton (2008) test with structural breaks, both τ_n (–2.992; p = 0.001) and φ_n (–3.349; p = 0.000) are significant at the 1% level, indicating a long-run cointegration relationship among the variables despite the presence of structural breaks. The results confirm that the cointegration relationship remains valid even after accounting for country heterogeneity and structural shifts. Estimated break dates for each country are presented in Table 7.

Table 7. Estimated break dates

Country	Break Point	Break Date	Country	Break Point	Break Date
ARG	2	≈ 2001	**JPN**	16	≈ 2015
BRA	17	≈ 2016	**MEX**	18	≈ 2017
CAN	17	≈ 2016	**RUS**	15	≈ 2014
CHN	3	≈ 2002	**ZAF**	3	≈ 2002
FRA	7	≈ 2006	**KOR**	17	≈ 2016
DEU	4	≈ 2003	**GBR**	6	≈ 2005
IND	9	≈ 2008	**USA**	13	≈ 2012

As illustrated in Table 7, the findings confirm the existence of a long-run cointegration relationship among the variables, which remains valid despite the presence of structural breaks. Most estimated break dates cluster between 2001-2008 and 2015-2017, periods corresponding to global financial crises and waves of digital transformation across G20 economies.

3.5. CCEMG and AMG long-run estimation models

In panel data analyses, second-generation estimators that account for cross-sectional dependence and heterogeneity enable more reliable estimation of long-run coefficients. In this context, two different second-generation panel estimators are employed in the study: CCEMG and AMG.

The CCEMG estimator, developed by Pesaran (2006), addresses potential cross-sectional dependence caused by unobserved common factors and global shocks by including a vector of common effects (f_t) and their loadings (λ_i) into the model. For each cross-sectional unit, the model is expressed as Equation (14):

$$A_{it} = \delta_i + d_t'\gamma_i + \epsilon_{it} \tag{14}$$

In Equation (14), d_t represents observed common effects, while f_t (not explicitly shown) denotes unobserved common effects. The CCEMG method calculates the overall panel coefficient as the average of the coefficients obtained for each cross-section, as shown in Equation (15):

$$\gamma_{CCEMG}' = \frac{1}{N}\sum_{i=1}^{N}\gamma_i' \tag{15}$$

This approach preserves individual heterogeneity while mitigating the impact of cross-sectional dependence. It produces consistent results even in small samples by reducing the effects of global shocks such as financial crises or technological disruptions (Pesaran 2006; Pesaran and Tosetti 2011).

The AMG estimator, introduced by Eberhardt and Bond (2009), similarly accounts for cross-sectional dependence and heterogeneity when estimating long-run coefficients across the panel. It extends the CCE-MG framework by incorporating a common dynamic process through a "time-dummy trend" that captures unobserved common components. The AMG estimator proposed by Eberhardt and Teal (2010) is expressed as Equation (16):

$$A_{it} = \beta_i + \gamma_i' G_{it} + \lambda_t + u_{it} \qquad \gamma_{AMG}' = \frac{1}{N}\sum_{i=1}^{N}\gamma_i' \tag{16}$$

In Equation (16), G_{it} denotes the vector of explanatory variables, and λ_t represents the common time effect across all units. This estimator provides robust long-run relationships, particularly for panels affected by common trends or structural changes (Eberhardt and Bond 2009; Eberhardt and Teal 2010).

Table 8. Long-Run estimation results

	CCEMG			**AMG**		
Variables	**Coef.**	**SE**	**p-value**	**Coef.**	**SE**	**p-value**
LNICT	-0.546	0.387	0.158	-0.739^{*}	0.397	0.063
LNTECIN	0.410	0.497	0.409	0.373	0.647	0.564
LNDIJIT	-0.222	0.478	0.642	-0.364^{**}	0.166	0.028
LNGDP	-1.151	1.744	0.509	-2.584^{***}	0.378	0.000

Note: ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

According to the long-run estimation results presented in Table 8, the coefficients of LNICT and LNDIJIT are negative, LNTECIN is positive, and LNGDP is negative in both models. While none of the variables are statistically significant in the CCEMG model, digitalisation (DIJIT) and economic growth (GDP) are statistically significant in the AMG model. Therefore, in the long run, digitalisation and economic size are identified as the main determinants significantly affecting sustainable development (SDG) among G20 countries, with both exhibiting negative long-run effects.

3.6. Panel causality test

The panel causality test developed by Dumitrescu and Hurlin (2012) allows for the analysis of the direction of causality between variables under a heterogeneous panel structure. This test is an extension of the classical Granger causality approach to panel data and can account for both cross-sectional dependence and heterogeneity across units. It is applicable in cases where either $T > N$ (time dimension greater than cross-section) or $N > T$, and it remains valid for unbalanced panels as well (Gholami, 2006). The baseline model of the Dumitrescu-Hurlin test is expressed in Equation (17):

$$Y_{it} = \alpha_i + \sum_{k=1}^{K} \gamma_i^{(k)} Y_{i,t-k} + \sum_{k=1}^{K} \beta_i^{(k)} X_{i,t-k} + \varepsilon_{it} \tag{17}$$

In Equation (17), $i = 1, \dots, N$ denotes the cross-sectional units, $t = 1, \dots, T$ denotes time, K is the lag length, and α_i represents the individual fixed effect. The model assumes a common lag order K for all units in the panel. The hypotheses are formulated as follows:

$$H_0: \beta_i^{(k)} = 0 \text{ No causality exists.}$$

$$H_1: \beta_i^{(k)} \neq 0 \text{ At least one unit exhibits causality.}$$

The panel-level test statistic is calculated by averaging the individual Wald statistics across all cross-sections. Dumitrescu and Hurlin (2012) define two statistics, as shown in Equations (18) and Equation (19):

$$W_{N,T} = \frac{1}{N} \sum_{i=1}^{N} W_{i,T} \tag{18}$$

$$Z_N = \frac{\sqrt{N}\left(W_{N,T} - N^{-1} \sum_{i=1}^{N} E(W_{i,T})\right)}{\sqrt{N^{-1} \sum_{i=1}^{N} Var(W_{i,T})}} \overset{N \to \infty}{\rightarrow} N(0,1) \tag{19}$$

When the absolute value of Z_N exceeds the critical value, the null hypothesis H_0 is rejected, indicating the existence of a causal relationship between the variables.

Table 9. Dumitrescu-Hurlin panel causality tests

Null Hypothesis:	W-Stat.	Zbar-Stat.	Prob.
LNICT ≠> SDG	4.47586	2.90368	**0.0037**
SDG ≠> LNICT	5.11365	3.76806	**0.0002**
LNTECIN ≠> SDG	2.76319	0.58256	0.5602
SDG ≠> LNTECIN	2.59226	0.35092	0.7257
LNDIJIT ≠> SDG	4.97793	3.58412	**0.0003**
SDG ≠> LNDIJIT	6.94289	6.24716	**0.0000**
LNGDP ≠> SDG	5.92445	4.86690	**0.0000**
SDG ≠> LNGDP	3.10728	1.04890	0.2942

Note: The symbolic expression "≠>" means that variable X does not cause variable Y. Lags = 2.

According to the results of the Dumitrescu-Hurlin (2012) panel causality test presented in Table 9, bidirectional causality is observed between LNICT and SDG, as well as between LNDIJIT and SDG. Additionally, a unidirectional causality running from LNGDP to SDG is identified. No statistically significant causal relationships are found among the other variable pairs.

4. Discussion

The empirical findings of this study reveal the long-run effects of digitalisation, information and communication technologies (ICT), technological innovation, and economic growth on sustainable development. The results are interpreted based on the long-run estimations from the CCEMG and AMG models and the causality relationships identified by the Dumitrescu-Hurlin panel causality test.

According to the long-run estimation results (Table 8), the coefficients of LNICT and LNDIJIT are negative, LNTECIN is positive, and LNGDP is negative in both models. In the AMG model, digitalisation (LNDIJIT) and economic growth (LNGDP) are statistically significant, indicating that digitalisation and economic size are the key long-term determinants of sustainable development. These findings are consistent with Bocean (2025) and Fernández-Portillo et al. (2019), who reported that digitalisation enhances sustainable development through improved economic performance in the European Union. However, the negative and statistically insignificant coefficient of ICT exports partially diverges from Zhao et al. (2022) and Gürler (2023). This discrepancy may arise from the heterogeneous nature of ICT impacts across G20 countries and the differing levels of technological openness among them.

The significant negative coefficient of LNDIJIT aligns with Kong et al. (2023), who emphasized that digitalisation, while promoting economic growth, can exacerbate income inequality. This result implies that digital transformation does not always produce uniformly positive outcomes and may, in highly digitalised economies, negatively affect social sustainability by deepening inequality. Furthermore, the results of the Westerlund-Edgerton (2008) panel cointegration test with structural breaks (Table 6) confirm the existence of a long-run equilibrium relationship among the series despite structural shifts. This finding supports the conclusions of Balsalobre-Lorente et al. (2025) and Yang et al. (2022), both of which highlight that digitalisation and technological innovation reinforce the long-term balance between environmental sustainability and economic growth.

The results of the Dumitrescu-Hurlin panel causality test (Table 9) reveal bidirectional causality between LNICT ↔ SDG and LNDIJIT ↔ SDG, and a unidirectional causality running from LNGDP → SDG. These findings indicate a mutual and reinforcing relationship between digitalisation, ICT activities, and sustainable development, consistent with He et al. (2024) and Yeerken and Feng (2024). By contrast, no causality is observed for technological innovation (LNTECIN), suggesting that patent-based indicators may have limited capacity to explain variations in sustainable development outcomes.

Overall, the findings underscore the significant role of digitalisation and economic growth in driving sustainable development, while the effects of ICT exports and technological innovation vary depending on country heterogeneity and structural breaks. This pattern supports the literature on the dual nature of digital transformation, which can act as both an enabler and a disruptor of sustainability (Alraja et al. 2023; Georgieva and Aleksandrova 2025). For G20 economies, ensuring that digitalisation contributes positively to sustainable development requires not only investments in digital infrastructure but also the strengthening of institutional capacity and the adoption of inclusive policy frameworks.

The Sustainable Development Goals (SDG) index has a composite structure that includes economic, social, and environmental dimensions. Because of this, the overall relationship between digitalisation and sustainable development may hide different effects across these dimensions. Digitalisation can support economic and social sustainability by increasing efficiency, innovation, and inclusion. However, its environmental effect is mixed. Higher energy demand, data storage, and electronic waste can weaken the positive outcomes. Future studies should separate the SDG index into subdimensions. This would help identify whether digitalisation mainly improves economic or social goals, or whether it also supports environmental sustainability.

The insignificant effect of ICT exports also needs more attention. This result may reflect major differences in digital trade capacity, innovation ecosystems, and infrastructure among G20 economies. In some countries, ICT exports create knowledge spillovers and improve competitiveness. In others, weak institutions or low innovation levels limit these gains. ICT exports may also have indirect effects through human capital or technology transfer, which aggregate indicators cannot fully capture. Future research could include new variables, such as digital intensity, e-commerce penetration, or digital service trade. These indicators would give a clearer and more balanced picture of how digital openness interacts with sustainability outcomes.

In short, the results highlight the need for a more detailed approach to measure the effects of digitalisation. Understanding which sustainability dimensions benefit the most will help policymakers design more focused and inclusive digital strategies. The following section presents the policy implications and future research directions derived from these findings.

5. Conclusion

This study examined the effects of ICT exports, digitalisation, technological innovation, and economic growth on sustainable development in G20 countries for the period 2000-2021. Second-generation panel data methods were employed by considering cross-sectional dependence and structural breaks. The findings indicate the presence of heterogeneity among countries and suggest that the variables are sensitive to common shocks. The results confirm the existence of a long-run cointegration relationship among the variables.

The Westerlund-Edgerton (2008) panel cointegration test with structural breaks shows that, despite structural changes, the variables move together in the long term. This implies that sustainable development maintains a long-run equilibrium relationship with the dynamics of digital transformation, technology, and economic growth. According to the long-run estimation results, digitalisation and economic size emerge as significant determinants of sustainable development. The negative coefficient of digitalisation suggests that, in some countries, the digital transformation has not produced the expected positive effects on sustainability. This may result from differences in technological advancement levels among G20 economies. The positive influence of economic growth highlights that achieving sustainable development goals is closely linked to financial capacity.

The causality analysis reveals bidirectional relationships between ICT, digitalisation, and sustainable development, suggesting a mutually reinforcing interaction. This means that digital transformation supports sustainable development, while sustainability objectives, in turn, stimulate digitalisation. The unidirectional causality from economic growth to sustainable development indicates that growth serves as a prerequisite for sustainable progress. Overall, the results underline that digitalisation and economic growth are key drivers of sustainable development, while the effects of ICT exports and technological innovation vary depending on country-specific structural characteristics. This finding implies that digital transformation policies cannot be explained by a single model. Each country should design strategies consistent with its own technological capacity and institutional framework.

6. Policy implications

The findings of this study provide several important insights for policymakers seeking to harmonise digital transformation with sustainable development objectives in G20 economies. The results highlight that while digitalisation and economic growth are key drivers of sustainable development, their effects differ across countries due to technological capacity, institutional quality, and environmental policy frameworks. Therefore, digital transformation strategies must be aligned with long-term sustainability goals through multidimensional policy coordination.

First, governments should pursue inclusive digital infrastructure development to ensure that the benefits of digitalisation reach all regions and social groups. Expanding broadband access, strengthening digital literacy programs, and closing the digital divide are crucial to achieving both social and economic sustainability. Second, technological innovation policies must explicitly incorporate environmental and social dimensions. Promoting green technologies, encouraging energy-efficient production systems, and linking patent incentives to sustainability-oriented outcomes can significantly improve resource efficiency and reduce environmental externalities. Third, to enhance the contribution of ICT to sustainable development, high value-added digital services should be prioritised. The digital economy must be integrated not only into production but also into education, governance, and public service delivery. ICT should be viewed as a transformative tool that fosters inclusive, resilient, and environmentally responsible growth. Fourth, economic growth strategies should be designed within an environmentally sensitive framework that promotes renewable energy investments, supports circular economy practices, and ensures responsible consumption. In this context, aligning growth targets with sustainability principles will help reduce the trade-offs between digital expansion and environmental quality.

Finally, the effectiveness of digitalisation depends on strong institutional and ethical frameworks. Policymakers must ensure transparent data governance, cybersecurity, and ethical AI use. Strengthening institutional capacity, promoting accountability, and adopting inclusive digital regulations are essential to sustaining the long-term balance between digital progress and social welfare.

7. Limitations and directions for future research

Although this study contributes to the understanding of the nexus between digitalisation and sustainable development, several limitations provide opportunities for further research:

- *Composite Nature of the SDG Index:* The SDG index aggregates economic, social, and environmental dimensions. Future studies could decompose it to identify which specific sustainability pillars are most affected by digitalisation and ICT exports.
- *Measurement of Digitalisation:* ICT exports and patent-based indicators may not fully capture the multidimensional aspects of digital transformation. Alternative measures such as digital intensity indices, digital service trade, or e-commerce activity could be incorporated in future models.
- *Cross-Country Heterogeneity:* This study uses a panel of G20 economies; however, country-level variations remain important. Comparative or cluster analyses could reveal how institutional capacity and policy environments shape the digitalisation–sustainability relationship.
- *Dynamic and Nonlinear Interactions:* Future studies might explore nonlinear or regime-switching approaches to capture asymmetric and time-varying effects of digitalisation on sustainability under different policy or technological regimes.
- *Policy Implementation and Governance Aspects:* Further empirical work could examine how governance quality, regulatory efficiency, and international cooperation influence the success of digital transformation policies in advancing sustainable 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.

Acknowledgments

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

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Journal of Sustainable Digital Futures 2025 1(2)

Journal of Sustainable Digital Futures

journal homepage: https://jsdf.org.tr/

Artificial intelligence and ESG: Exploring dynamic interdependencies in sustainable digital futures

Hakan YILDIRIM[1]

HIGHLIGHTS

[1] Mersin University, Erdemli Academy of Applied Technology and Business Administration, Mersin, Türkiye, hakanyildirim@mersin.edu.tr

ARTICLE INFO

Keywords:

Artificial intelligence
ESG
Quantile-on-Quantile
Connectedness

ABSTRACT

This study analyzes the connectedness dynamics between artificial intelligence (AI)-themed indices and the global environmental, social, and governance (ESG) index within a nonlinear and regime-sensitive framework. Using daily data for the 2018-2025 period, the Quantile-on-Quantile Connectedness (QQC) approach is employed to examine how information transmission between AI and ESG markets varies across different distributional states. The empirical findings indicate that under adverse market regimes, AI indices predominantly act as receivers of information, while the ESG index assumes a transmitter role. In contrast, during periods associated with more favorable market conditions, the direction of information flow reverses, and AI indices tend to function as net transmitters influencing ESG performance. These results reveal that the connectedness between AI and ESG indices is highly nonlinear, asymmetric, and strongly dependent on market regimes rather than being stable over time. Overall, the findings provide relevant insights for investors, policymakers, and financial regulators by highlighting how AI and sustainability-oriented markets alternately shape information flows under stress and non-stress conditions, thereby offering a regime-aware framework for portfolio diversification, risk monitoring, and financial stability assessment.

1. Introduction

In recent years, financial markets have undergone a profound transformation driven by technology-centered innovations and the growing prominence of sustainability-oriented investments. On one hand, investment strategies grounded in ESG criteria have evolved from being merely ethical preferences to becoming critical components of long-term return generation and risk management (Kräussl 2024; Lunawat 2025). On the other hand, AI transformations are reshaping capital markets and generating a structural shift within the financial sector. As AI continues to define the trajectory of technological development and innovation, investor interest in firms that lead advancements in this domain has intensified (Poutachidou and Koulis 2025). Particularly since late 2022, the rapid expansion of generative AI has substantially heightened investors' attention toward AI-based firms and AI-themed portfolios (Qin 2025). This surge has made the interaction between AI-based financial indicators and sustainability-oriented indices increasingly visible in terms of investor behavior and overall market dynamics.

Received 21 November 2025; Received in revised from 21 December 2025; Accepted 28 December 2025
Available online 30 December 2025

One of the primary driving forces behind this transformation in financial markets is digital innovation. Digital innovation is defined as the effective integration of digital technologies into business processes and the development of novel digital products (Nambisan et al. 2017). With its strong potential to promote sustainable business practices, digital innovation enhances operational efficiency, helps optimize resource utilization, enables remote-work flexibility, and enhances transparency, which in turn supports better environmental performance, stronger social responsibility, and more effective governance practices. Moreover, by reshaping how firms interact with their external environment, it influences stakeholder relations and competitive dynamics (Tian et al. 2022). This micro-level transformation gradually generates macro-level reflections in financial markets, and this observation aligns with studies demonstrating the impact of digital transformation on corporate environmental performance (Wang et al. 2025). In this regard, digital innovation can indirectly influence both the direction and the intensity of information flows between technology-based investment indices and sustainability indices.

Digital transformation also plays a critical role in improving environmental performance. Advanced digital technologies enable firms to monitor and manage environmental indicators—such as energy consumption and emissions—in real time, thereby reducing environmental impacts by increasing resource-use efficiency within production processes (Nguyen et al. 2020). Moreover, digitalization facilitates the adoption and diffusion of green technological innovations, encouraging environmentally friendly production practices (Chen and Xie 2022). The information transparency and external oversight made possible by digital technologies also contribute to enhanced corporate environmental responsibility, prompting firms to adopt more sustainable and accountable strategies (Hao et al. 2023; He et al. 2022). Therefore, the positive influence of digital innovation on ESG performance is not confined solely to the firm level; it can also manifest in the interaction dynamics between indices, reflecting the broader implications of technological transformation in financial markets.

Within this framework, AI, as a major pillar of digital innovation, has become an important area of application that can meaningfully affect ESG performance. AI applications can directly affect multiple dimensions of ESG performance, ranging from optimizing energy consumption and waste management to strengthening diversity and inclusion through unbiased decision-making processes (Vinuesa et al. 2020). Therefore, the interaction between generative AI and sustainability should be viewed not merely as a technological innovation but also as a strategic dynamic shaping the future of financial markets. The reflections of AI-driven technological progress in financial markets can be observed concretely through AI indices, and the interaction between these indices and ESG indicators serves as a critical signal for understanding the capacity of digital transformation to create sustainable value in capital markets.

On the other hand, during the same period, the concept of sustainability has also risen to a central position among firms' strategic priorities. This trend is driven by the increasing emphasis placed by international institutions—such as the United Nations and the European Union—on not only environmental responsibility but also social welfare and inclusive development (Farahani et al. 2017). Consequently, in a period when technological transformation gains momentum on one side and sustainability-oriented policies strengthens on the other, a new interaction domain emerges at the intersection of these two areas. At this point, the connectedness between AI and ESG indicators becomes crucial for identifying investor preferences and achieving portfolio diversification. Thus, the AI–ESG nexus constitutes a relatively new and increasingly specific field within the literature. In sum, examining the impact of digital transformation—and AI technologies as one of its core components—on sustainability is also essential for fostering the sustainable transformation of the economy and society (Wang et al. 2025a).

The interaction between AI-based investment instruments and ESG-oriented financial indices is primarily shaped through information transmission processes and investor sentiment channels. While innovation-driven AI assets tend to respond rapidly to changes in technological expectations and information flows, ESG-oriented assets are more closely associated with policy developments and long-term risk assessments, thereby exhibiting relatively slower adjustment dynamics (Abdelkader and Si Mohammed 2025). Moreover, the fact that financial asset prices are determined not only by fundamental factors but also by shifts in expectations and risk perceptions that vary across market conditions renders investor sentiment a key mechanism governing the direction and intensity of information spillovers between these two market segments (Barberis et al. 1998; Baker and Wurgler 2006). In this context, the connectedness between AI and ESG indices is highly likely to display a time-varying, asymmetric, and regime-sensitive structure.

A segment of the existing literature examines the performance and behavior of AI-based investment instruments (Poutachidou and Koulis 2025; Qin 2025), while another segment investigates the role of AI tools in financial behavior within the ESG framework (Abdalmuttaleb et al. 2022). Lim (2024), in his study analyzing research domains related to ESG-AI trends in the finance literature, identifies that the strongest focus lies in the determination of trading and investment areas. Systematic research on ESG investments, on the other hand, generally concentrates on themes such as risk–return relationships, portfolio diversification, and corporate governance (Kräussl et al. 2024). This pattern indicates the need for a regime-sensitive analytical framework that can reveal how the AI-ESG interaction evolves, particularly under extreme market conditions. In this respect, the direction, magnitude, and asymmetric structure of information flow between AI-based indices and ESG indices emerge as a relatively unexplored area in the contemporary literature.

The primary objective of this study is to examine the connectedness among AI indices, specifically the Nasdaq CTA Artificial Intelligence Index (AI_NASDAQ) and the Global X Artificial Intelligence & Technology ETF (AIQ) and the MSCI World ESG Leaders Index, which is employed as the sustainability indicator, using daily data from the period 1 November 2018 to 27 October 2025. The analysis utilizes the QQC approach developed by Gabauer and Stenfors (2024). Rather than focusing solely on average relationships, the study aims to reveal in detail how different market regimes (e.g., stress conditions such as the COVID-19 period) shape shock transmission between the two markets at various quantile levels. In doing so, the nonlinear, asymmetric, and regime-dependent structure of the interaction between AI markets and the ESG index representing global sustainability performance is comprehensively evaluated. The resulting framework seeks to enhance the understanding of the dynamic relationship between technology-based and sustainability-based financial markets.

This study fills an important gap in the literature examining the financial interaction between AI indices and the ESG index, as most existing research focuses on the impact of AI on ESG performance at the firm level, while the relationship between market indices is addressed only to a limited extent and predominantly through linear methods. By employing the QQC approach, this study offers a novel contribution to the literature through its quantile-based, regime-dependent, and nonlinear examination of this relationship. The QQC methodology enables a detailed exploration of how AI and ESG markets interact during periods of low, normal, and high volatility, thereby making visible the tail connectedness structures, asymmetries, and crisis-specific dynamics that conventional methods typically overlook. This distinctive analytical framework allows investors to conduct more accurate risk assessments for portfolio diversification strategies, enables policymakers to design coordinated technology and sustainability policies, and helps firms better evaluate the indirect financial implications of AI investments on sustainability performance. In sum, by analyzing the interaction between AI and ESG markets through a multidimensional perspective, this study provides a substantial and innovative contribution to both the theoretical and empirical literature.

Accordingly, the subsequent sections of the study are structured as follows. Section 2 provides a comprehensive review of the existing literature addressing the relationship between AI and ESG. Section 3 presents the methodological framework of the research and introduces the data set, variables, and empirical approach in detail. Section 4 reports the findings of the quantile-level connectedness analyses obtained through the implementation of the QQC approach. In Section 5, the findings are discussed from a multidimensional and holistic perspective. Section 6 develops policy implications, and finally, Section 7 presents the limitations of the study and offers directions for future research.

2. Literature review

AI, which has become one of the most prominent concepts of the modern world and whose significance, applicability, and implications are frequently debated, has evolved into a transformative innovation shaping numerous sectors and structures (Vinuesa et al. 2020). For instance, Acemoglu and Restrepo (2018) examine AI's two opposing effects—namely the displacement effect and the productivity effect—on global productivity; Bolukbasi et al. (2016) focus on issues of gender equality and inclusion; Norouzzadeh et al. (2018) explore its impacts on ecological systems and the environment;

Wang et al. (2025a) and Nishant et al. (2020) investigate implications for sustainability; and Vinuesa et al. (2020) assess its direct influence on the Sustainable Development Goals. These studies consistently demonstrate that AI has substantial and wide-ranging effects. Such broad impacts of AI become even more visible in finance, which is among the sectors experiencing the most intensive digitalization.

Digitalization is one of the domains with which the financial sector interacts most intensively. In particular, with the growing influence of the millennial generation in both the business world and consumer markets, technologies such as cloud services, open-source software, AI, and mobile devices have rapidly proliferated (Hill 2018). With the growing reliance on digital financial services such as mobile payments, access to the financial system has widened considerably, helping to improve inclusion among low-income populations (Lee et al. 2021; Siddiqui and Siddiqui 2020). It is widely acknowledged that the financial sector—being one of the industry's most closely aligned with technological development—is among the areas in which AI is expected to exert the strongest impact. Indeed, the effects of AI in finance have been the subject of extensive research, and continue to attract substantial academic attention (Bredt 2019; Biallas and O'Neill 2020; Milana and Ashta 2021). The principal functions of AI in the financial sector include enhancing the quality of products and services through advanced analytical insights, and enabling more efficient applications such as fraud detection, anti–money laundering (Bredt 2019), and credit rating (Plawiak et al. 2019). Additionally, many studies examining AI applications in accounting and finance have focused on portfolio optimization, risk management, and asset pricing, further underscoring the sector's extensive integration with AI-driven tools and processes (Ertenlice and Kalayci 2018).

One of the key reflections of this transformation in financial markets is the emergence of thematic AI indices and AI-focused ETFs. Consequently, these instruments have increasingly become the subject of academic investigation. For example, Poutachidou and Koulis (2025) examine 15 AI-focused ETFs in the United States and show that the performance of these funds is largely driven by asset selection, while investment style and the degree of active–passive management differ substantially across funds. In another study, Belhouichet et al. (2025) employ a QVAR-based tail connectedness analysis and demonstrate that AI and robotics ETFs act as net transmitters of market shocks—together with the S&P 500—and that this effect is particularly concentrated under extreme market conditions. According to their findings, AI-based ETFs are becoming increasingly influential within the financial system, both in terms of investment-style characteristics and risk-spillover mechanisms.

ESG is a form of investment that creates long-term social, environmental, and economic value (Iannone et al. 2025). In the literature on the financial performance of ESG indices—particularly during periods of structural disruptions such as wars and pandemics (Broadstock et al. 2021; De Renzis et al. 2024; Naffa and Dudás 2024), it is frequently argued that firms with high ESG scores exhibit lower risk, more stable cash flows, and stronger long-term performance (Giese and Shah 2025). For this reason, ESG stocks tend to be less prone to investor withdrawal during crisis periods, especially among value-oriented investors (Lashkaripour 2023).

Evidence indicating that AI strengthens sustainability performance has become increasingly clear in the literature. Liu et al. (2025) show that AI adoption generally enhances the environmental, social, and governance dimensions of Chinese firms, while Yu et al. (2025) similarly demonstrate that firms' AI capabilities significantly improve ESG performance through more efficient resource allocation and supply chain optimization. Consistent with these findings, the literature emphasizes that AI enhances ESG performance through multiple mechanisms, including energy management (Coulson et al. 1987), emission reduction (Ding et al. 2024), resource optimization (Almansour 2023), strengthening corporate environmental reputation (Dauvergne 2022), improving stakeholder (customer) experiences (Ameen et al. 2021), and supporting governance processes (Reddy et al. 2020).

Although the literature examining the impact of AI on ESG performance—predominantly at the firm level—has expanded rapidly, empirical evidence on how AI-ESG interactions unfold at the market level remains limited. Most existing studies rely on linear and mean-based methodologies, which are insufficient to capture regime-specific, asymmetric, and tail-sensitive information transmission mechanisms that become particularly salient during periods of heightened market stress. Against this background, this study focuses on addressing this gap by examining the interaction between AI-themed financial indices and ESG-oriented indices within a market-level, regime-sensitive, and nonlinear analytical framework.

3. Data and methodology

Classical econometric methods predominantly focus on conditional mean effects and therefore tend to overlook asymmetric and directional information transmissions that emerge under tail market conditions (Diebold and Yılmaz 2014; Engle et al. 2020). For this reason, quantile-based approaches have gained increasing prominence in the finance literature and have become widely adopted in empirical studies (Cech and Baruník 2017; Armah and Amewu 2024; Hadad et al. 2024).

In recent years, notable methodological advances have been made toward empirically capturing the complex relationships inherent in financial systems. In particular, quantile connectedness models have enabled the analysis of information spillovers across variables not only around the mean but also at different quantile levels. Building on these advancements, the QQC approach introduced by Gabauer and Stenfors (2024) allows the transmission mechanism between quantiles to be identified in terms of both direction and magnitude, rather than restricting the analysis to a single quantile.

3.1. Data set

In this study, the connectedness between AI-related financial assets and ESG-oriented investment indices is examined at the global level using daily data covering the period from 1 November 2018 to 27 October 2025. AI-related market activity is represented by two distinct AI-based investment indicators: the Nasdaq CTA Artificial Intelligence Index (AI_NASDAQ), which tracks the performance of companies engaged in the development and application of AI technologies across the technology, industrial, healthcare, and other economic sectors; and the Global X Artificial Intelligence & Technology ETF (AIQ), which encompasses firms expected to benefit from the development and utilization of AI-based products and services, as well as hardware providers that enable the use of AI in big data analytics. Data for both indices are obtained from www.investing.com.

Sustainability-oriented market dynamics are captured using the MSCI World ESG Leaders Index, a global benchmark composed of companies exhibiting high ESG performance relative to their sector peers. The index is constructed based on MSCI ESG ratings by selecting firms with superior ESG scores within each sector while maintaining market-capitalization weighting. This approach allows the index to represent a diversified global equity portfolio of companies with relatively strong ESG characteristics without deviating from a market-based index structure. Data for the index are obtained from www.msci.com.

To transform the time series to a stationary form and to allow for the interpretation of percentage changes, logarithmic transformations are applied. This transformation is particularly essential for detecting the propagation of nonlinear shocks. The logarithmic transformation is defined as in Equation (1):

$$\Delta lnX_t = ln(X_t) - ln(X_{t-1}) \tag{1}$$

The logarithmic difference transformation is applied not only to stabilize the variance of the AI_NASDAQ and AIQ series used in the analysis but also to allow the rates of change to be interpreted in percentage terms. In Figure 1, the upper panels display the returns of AI_NASDAQ and AIQ, while the lower panel presents the level values of the ESG index. An examination of the upper panels corresponding to AI reveals that both indices exhibit abrupt spikes, particularly during the 2020 COVID-19 period and after late 2023. These spikes indicate that the fluctuations observed during these periods are highly sensitive to shifts in investor sentiment and changes in market dynamics. In particular, the high-frequency volatility observed in the AI_NASDAQ index suggests a heightened sensitivity to systemic risk.

On the other hand, when the trend of the ESG index is examined, it shows an upward trajectory in the long run, albeit with short-term fluctuations. These fluctuations can be interpreted as evidence that ESG is influenced by global macroeconomic dynamics.

When Figure 1 is evaluated as a whole, it becomes apparent that the dynamic behavior of AI index returns and the ESG index varies across different sub-periods, particularly during episodes of heightened market stress. While AI index returns display pronounced variability and volatility clustering, the ESG index follows smoother trend dynamics accompanied by visible structural shifts over time. These differences suggest that the interaction between the two series is unlikely to be stable or homogeneous across market conditions. Accordingly, the dependence structure between AI and ESG indices may differ across various segments of their conditional distributions, indicating that analyses focusing solely on average effects may be insufficient. In this respect, the QQC approach provides an appropriate framework for capturing potential nonlinear, asymmetric, and regime-dependent connectedness patterns.

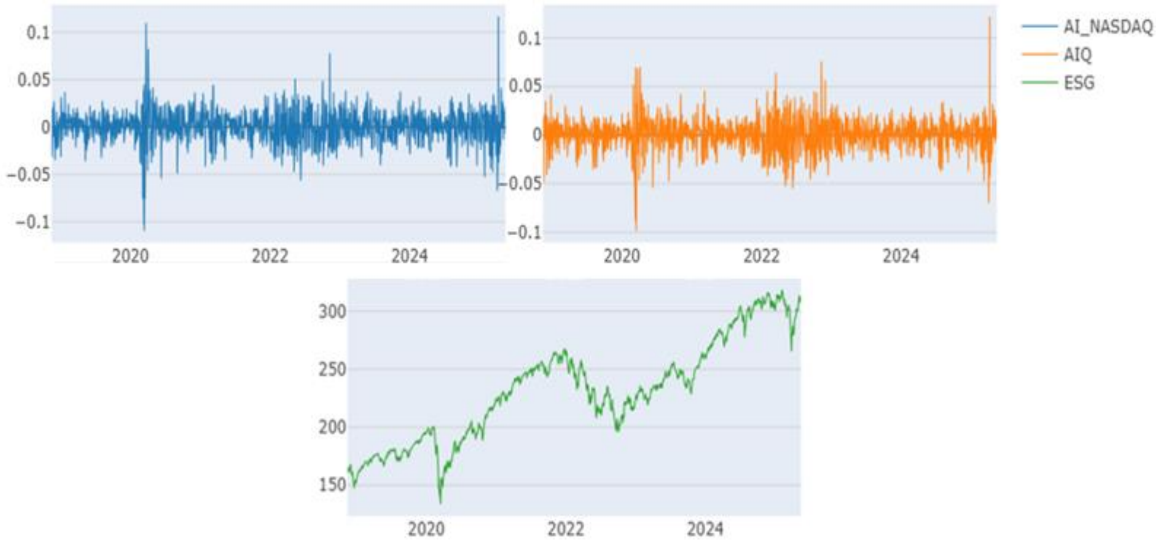

Figure 1. Return series of ESG and AI indices

Table 1 reports the descriptive statistics of the variables. The high excess kurtosis values observed across all series indicate leptokurtic distributions and pronounced tail behavior. The skewness statistics suggest that the return distributions are asymmetric, with AI_NASDAQ exhibiting positive skewness, while the ESG index displays pronounced negative skewness (–0.690).

The Jarque–Bera (JB) test results ($p < 0.01$) further confirm that the series do not satisfy the normality assumption. Taken together, the presence of asymmetry, heavy tails, deviations from normality, and time-varying volatility suggests that linear, mean-based methods may be inadequate for capturing the underlying dependence structure, thereby providing methodological support for the use of quantile-based and regime-sensitive approaches such as QQC.

Table 1. Descriptive statistics

	AI_NASDAQ	AIQ	ESG
Mean	0.000	0.000	0.089
Variance	0.001	0.001	5.185
Skewness	0.176*** (-0.004)	0.024 (-0.692)	-0.690*** (0.000)
Ex. Kurtosis	5.801*** (0.000)	5.750*** (0.000)	7.045*** (0.000)
JB	2292.180*** (0.000)	2244.640*** (0.000)	3497.469*** (0.000)
ERS	-4.661*** (0.000)	-4.375*** (0.000)	-16.668*** (0.000)
Q(10)	467.627*** (0.000)	536.570*** (0.000)	34.390*** (0.000)
Q^2(10)	1017.620*** (0.000)	885.609*** (0.000)	550.598*** (0.000)

Note: *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively

3.2. Methodology

Traditional dependence analyses typically focus on information transmission at the mean level and therefore overlook asymmetric and directional spillover effects that emerge during tail events (Diebold and Yılmaz 2014; Engle et al. 2020). However, as noted above, the AI-ESG relationships examined in this study exhibit nonlinear, threshold-driven, and quantile-sensitive dynamics. Accordingly, this study employs the QQC method developed by Gabauer and Stenfors (2024), which is a modern and robust approach for analyzing heterogeneous structures. The QQC approach investigates information transmission across different segments of the distribution at the quantile level and reveals directional connectedness within the system, thereby overcoming the limitations of traditional VAR-based models (Sim and Zhou 2015; Diebold and Yılmaz 2012; Chatziantoniou et al. 2021; Yıldırır Keser and Tarkun 2025). In other words, rather than focusing solely on a specific quantile (e.g., τ_1 = 0.05, τ_2 = 0.05), this new approach captures spillovers across different quantiles (e.g., τ_1 = 0.05, τ_2 = 0.95), thereby relaxing the assumption of positive correlation in time series (Evrim Mandacı et al. 2025).

Moreover, this method employs quantile-based Generalized Forecast Error Variance Decomposition (GFEVD), allowing the magnitude and direction of systemic risks to be measured and enabling the modeling of the distributional effects of shocks in a manner that is invariant to variable ordering (Diebold and Yılmaz 2012; Chatziantoniou et al. 2021; Hadad et al. 2024). The Quantile Vector Autoregressive model QVAR(p), which forms the foundation of the QQC framework, captures not only the temporal dependence of time series but also their asymmetric behavior across different quantile levels, thereby revealing heterogeneous interactions (Ando et al. 2022; White et al. 2015). The QQC method incorporates both the magnitude of shocks and their position within the distribution, enabling the construction of quantile-level information transfer maps and facilitating a detailed analysis of tail risk. Consequently, directional systemic dependence can be quantified (Gabauer and Stenfors 2024). In this regard, QQC is methodologically appropriate for analyzing the directional, nonlinear, and quantile-based relationships between AI and ESG indicators.

For a multivariate time series $y_t \in \mathbb{R}^N$, the quantile-VAR model is defined as follows in Equation (2) (Yıldırır Keser and Tarkun 2025):

$$Q_{\gamma t}(\tau \mid \mathcal{F}_{t-1}) = \sum_{p=1}^{p} \Phi_p(\tau)\, y_{t-p} + \varepsilon_t(\tau) \tag{2}$$

$Q_{\gamma t}(\tau \mid .)$, denotes the conditional estimate of y_t at quantile τ while $\mathcal{F}_{t-1}$ represents the information set available at time $t-1$, including the lagged values of the relevant variables. $\Phi_p(\tau)$ refers to the quantile-specific regression coefficients, and $\varepsilon_t(\tau)$ denotes the error term corresponding to each quantile level.

Within the Quantile-Based Connectedness framework grounded in GFEVD (Diebold and Yılmaz 2012; Gabauer and Stenfors 2024), the information transmission is defined as follows in Equation (3):

$$\theta^g{}_{ij}(\tau, h) = \frac{\sigma_{jj}{}^{-1} \sum_{k=0}^{h-1} (e_i{}' A_k(\tau) \Sigma e_j)^2}{\sum_{k=0}^{h-1} (e_i{}' A_k(\tau) \Sigma A_k(\tau)' e_i)} \tag{3}$$

In Equation (3), $\theta^g{}_{ij}(\tau, h)$ represents the generalized forecast error variance decomposition (GFEVD) for quantile level τ and forecast horizon h, measuring the contribution of variable j to variable i. $A_k(\tau)$, denotes the quantile-specific moving average coefficient matrices at lag k. e_i and e_j, represent the selector vectors that extract the i-th and j-th variables from the system, respectively. Σ denotes the error covariance matrix, and σ_{jj} represents the j-th diagonal element of Σ.

Accordingly, the Total Connectedness Index (TCI) is computed as follows in Equation (4):

$$TCI(\tau) = \frac{\sum_{i \neq j} \theta^g{}_{ij}(\tau, h)}{\sum_{ij} \theta^g{}_{ij}(\tau, h)} \times 100 \tag{4}$$

Net directional connectedness is represented in Equation (5):

$$NET_i(\tau) = \sum_{j \neq i} \theta^{g}{}_{ji}(\tau, h) - \sum_{j \neq i} \theta^{g}{}_{ij}(\tau, h) \tag{5}$$

When this value is positive, the variable acts as an information transmitter within the system; when it is negative, it serves as an information receiver. Unlike traditional VAR and DCC models, the QQC approach enables the simultaneous analysis of both the magnitude of shocks and the asymmetric structure of responses across different quantile levels. Owing to this capability, the nonlinear and directional connectedness between AI indices and the ESG index can be modeled in a more comprehensive manner.

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4. Empirical results

In this section of the study, the quantile-level reciprocal connectedness dynamics between the performances of AI indices and the ESG index are analyzed in detail. Owing to the QQC approach, not only mean-based relationships but also the dependence structures that emerge under extreme market conditions become visible. This method reveals regime-dependent and asymmetric connectedness patterns that traditional linear models fail to capture. Consequently, it enables a deeper understanding of how market behavior evolves across different quantiles.

Based on the TCI results in Figure 2, the connectedness between AIQ and ESG changes notably depending on the size of shocks (horizontal axis) and where the information lies within the distribution (vertical axis). The values displayed in the figure indicate that connectedness between the AI and ESG indices strengthens in the upper-tail regions of the conditional distribution, while remaining elevated also in the lower-tail states, with particularly high levels observed at extreme quantile combinations (e.g., 77.4% at 0.05×0.05 and 63.8% at 0.95×0.95). This demonstrates that the variables exhibit strong connectedness under both positive and negative tail scenarios. The high TCI observed in the lower-tail quantiles indicates that, under adverse market conditions, shocks propagate more easily and in a bidirectional manner. However, the pattern differs in the mid-quantiles: the weakening of connectedness in this region suggests that, under normal market conditions, information flow is more limited and is generally shaped by local dynamics. Taken together, the findings reveal that the AI-ESG connectedness is not linear; on the contrary, it is highly sensitive to market dynamics and exhibits a strongly nonlinear structure.

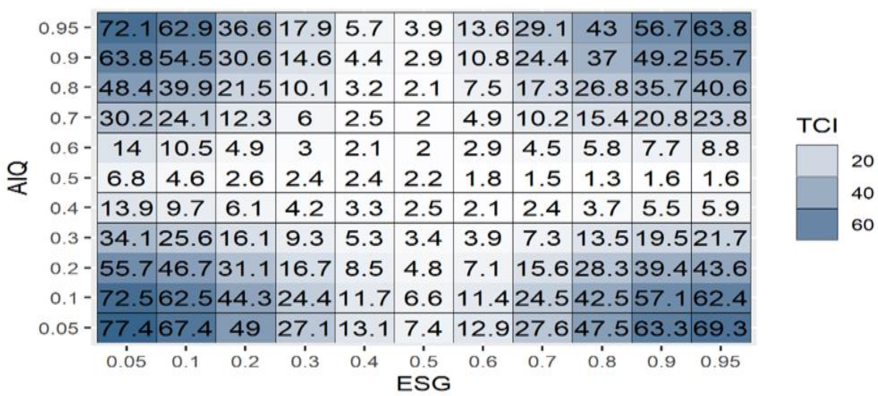

Figure 2. Quantile total connectedness indices for AIQ and ESG

Based on the TCI results in Figure 3, the connectedness between AI_NASDAQ and ESG varies systematically across different regions of the conditional distribution. The figure shows that overall connectedness intensifies under tail conditions (e.g., 78.3% at 0.05×0.05 and 61.6% at 0.95×0.95), indicating stronger interdependence during extreme distributional states. By contrast, connectedness weakens markedly around the central quantiles, suggesting that market interactions are more limited under relatively normal conditions.

Taken together, these patterns indicate that the AI-ESG relationship is not constant over time or across market regimes. Instead, the strength of connectedness is highly sensitive to distributional states, which cannot be adequately captured by linear or mean-based approaches. This provides direct empirical support for the use of a quantile-based and regime-sensitive framework such as QQC.

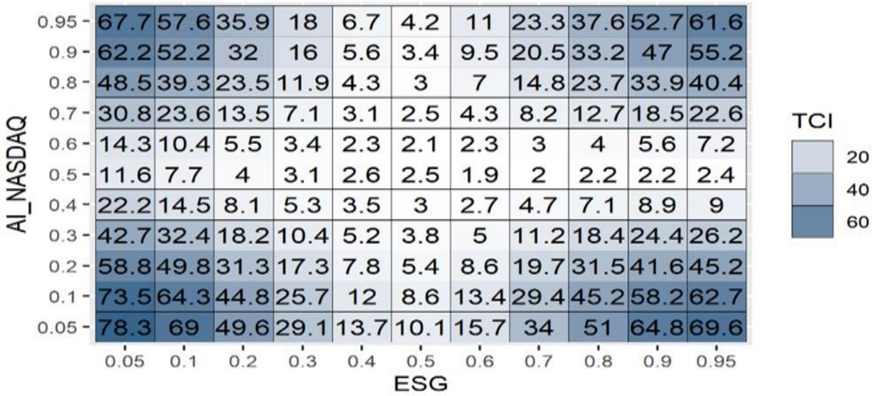

Figure 3. Quantile total connectedness indices for AI_NASDAQ and ESG

Figure 4 illustrates that the direction and magnitude of net connectedness between AIQ and ESG vary across quantiles, indicating a regime-dependent structure. The prevalence of negative net values in the lower quantiles suggests that AIQ predominantly acts as a net receiver of shocks during these states, implying that information transmission from ESG to AIQ is relatively stronger in this region of the distribution. In contrast, net values become partially positive in the upper quantiles, indicating that AIQ transitions into a net transmitter role, while the ESG index assumes a relatively more responsive position. The near-zero net values observed in the mid-quantiles point to weak or balanced directional interactions, suggesting that information flows are less pronounced under relatively moderate market conditions.

Taken together, these findings demonstrate that the direction of information transmission between AIQ and ESG is not constant, but varies systematically across quantiles, highlighting a nonlinear and regime-dependent connectedness structure.

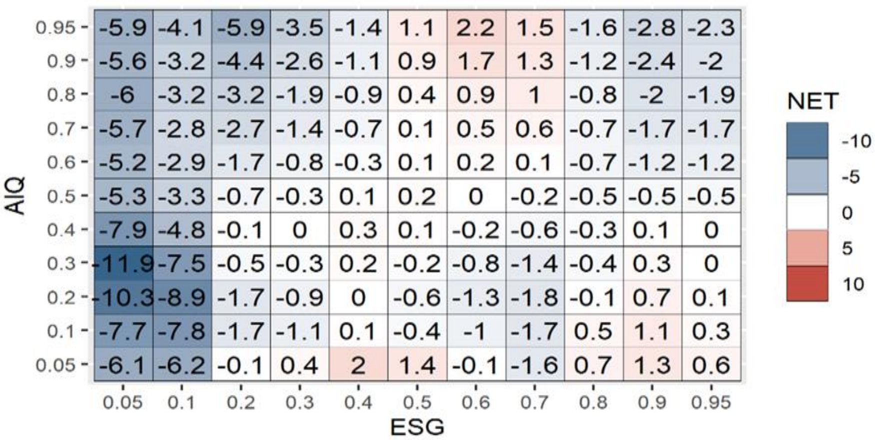

Figure 4. Net Quantile connectedness between AIQ and ESG

As illustrated in Figure 5, the quantile-based net directional connectedness between AI_NASDAQ and ESG varies markedly across quantiles, indicating a regime-dependent directional structure. The predominance of negative net values in the lower quantiles suggests that AI_NASDAQ mainly acts as a net receiver in this region of the distribution, implying relatively stronger information transmission from ESG to AI_NASDAQ under these states.

In contrast, net values turn positive in the upper quantiles, indicating that AI_NASDAQ assumes a net transmitter role, while ESG becomes relatively more responsive. The near-zero net values observed around the central quantiles point to weak or balanced directional interactions, suggesting the absence of a dominant information flow under moderate conditions. Overall, these findings indicate that the direction of information transmission between AI_NASDAQ and ESG is not constant, but changes systematically across quantiles, highlighting a nonlinear and regime-sensitive connectedness pattern that is fully consistent with the QQC framework.

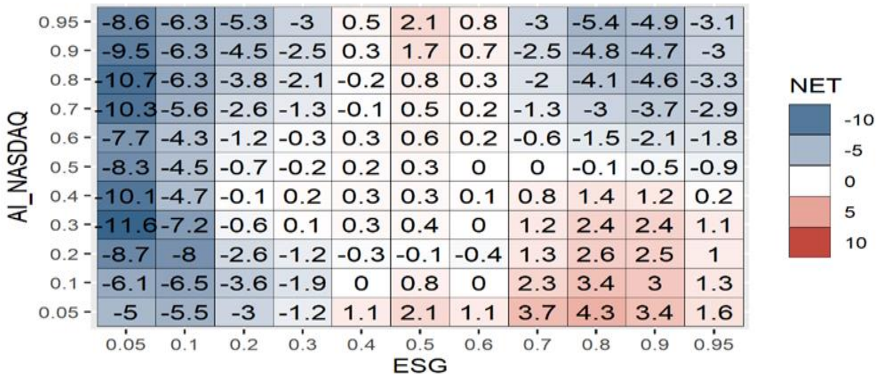

Figure 5. Net Quantile connectedness between AI_NASDAQ and ESG

According to the visual evidence presented in Figure 6, the information flow between AIQ and the ESG index varies over time, indicating a time-varying directional connectedness structure. In the graph, the green line (Direct TCI) represents information transmission from ESG to AIQ, the red line (Reverse TCI) represents information transmission from AIQ to ESG, and the blue line (ΔTCI = Direct − Reverse) captures the net directional dominance between the two markets. Positive values of ΔTCI indicate a relative dominance of ESG-to-AIQ transmission, whereas negative values indicate dominance in the opposite direction. During the 2020–2021 pandemic period, the Reverse TCI generally lies above the Direct TCI, and ΔTCI remains predominantly negative, indicating that AIQ tends to act as a net transmitter, while the ESG index assumes a more responsive role. This pattern suggests a temporary strengthening of AIQ-to-ESG information transmission during this period. In the post-2022 period, the difference between Direct and Reverse TCI narrows, and ΔTCI fluctuates around zero, pointing to a more balanced and less persistent directional structure of information transmission. During this phase, neither direction remains consistently dominant, although short-lived shifts continue to emerge.

Overall, these findings indicate that directional connectedness between AIQ and ESG is not stable over time, but evolves across different periods, consistent with a dynamic and regime-sensitive connectedness framework.

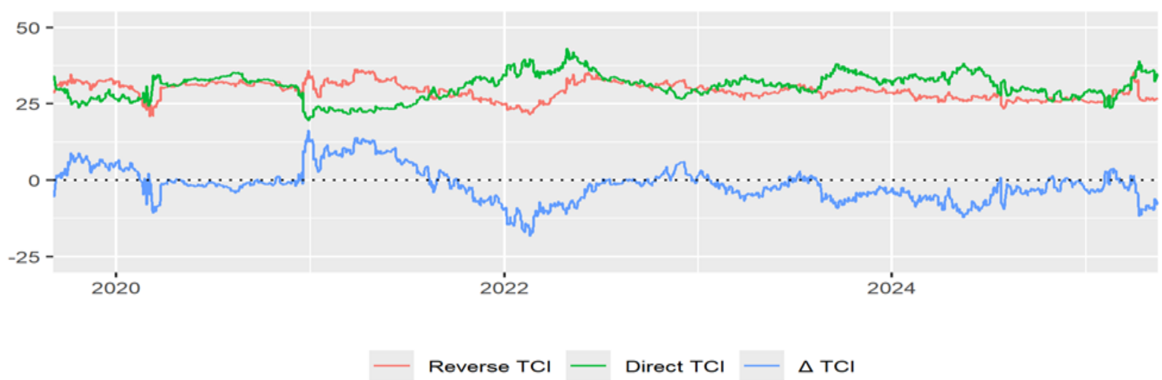

Figure 6. Direct and reverse total connectedness indices for AIQ and ESG

The visual evidence presented in Figure 7 shows that the information flow between AI_NASDAQ and the ESG index varies over time, indicating a time-varying directional connectedness structure. Periods in which ΔTCI takes positive values indicate a relative dominance of information transmission from ESG toward AI_NASDAQ, whereas negative ΔTCI values indicate dominance in the opposite direction, with AI_NASDAQ acting as a net transmitter. During the early part of the sample, the Reverse TCI generally lies above the direct TCI, and ΔTCI remains predominantly negative, suggesting that AI_NASDAQ more frequently assumes a net transmitter role, while ESG appears relatively more responsive. In later periods, the difference between direct and reverse TCI narrows, and ΔTCI fluctuates around zero, pointing to a more balanced and less persistent directional structure of information transmission. Although short-lived episodes of directional dominance continue to emerge, no single direction remains permanently dominant. Overall, these findings indicate that the connectedness between AI_NASDAQ and ESG is asymmetric and time-varying, and that the direction of information transmission changes across different periods, consistent with a regime-sensitive connectedness framework.

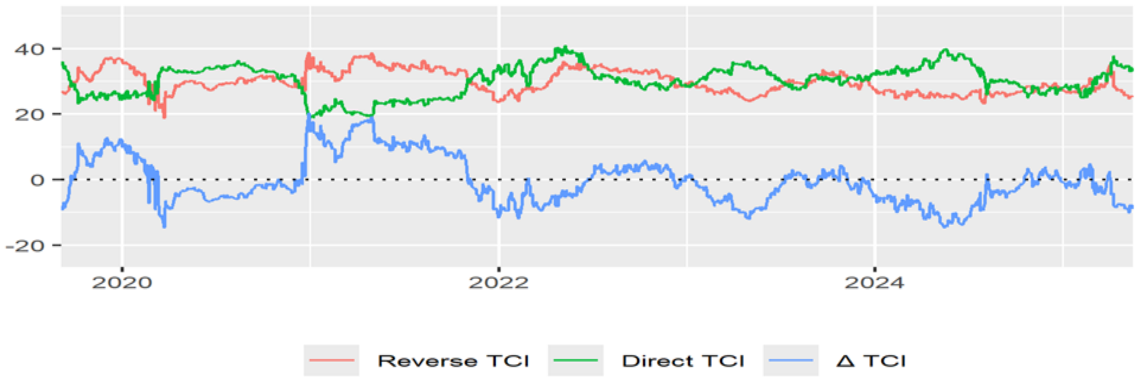

Figure 7. Direct and reverse total connectedness indices for AI_NASDAQ and ESG

5. Conclusion and discussion

This study examines the information flow between AI indices and the ESG index within a nonlinear, regime-sensitive, and asymmetric framework. By moving beyond mean-based analysis, the findings highlight that the dependence structure between AI and ESG markets is inherently state-dependent. The findings show that information diffusion differs substantially in both direction and magnitude under varying market conditions. Empirical results indicate that under adverse market regimes (lower-quantile states), the AI_NASDAQ and AIQ indices predominantly act as net receivers, while the ESG index assumes the role of an information transmitter. By contrast, during more optimistic market conditions, AI indices generally emerge as dominant transmitters of information, with the ESG index responding accordingly. This asymmetry suggests that risk- and sustainability-related signals become more influential during stressed market environments, whereas technology and innovation-driven expectations dominate under favorable conditions.

The results are consistent with prior studies emphasizing that information transmission within financial systems varies over time in both direction and intensity (Diebold and Yılmaz 2012; Baruník and Křehlík 2018). They also align with the literature highlighting the effectiveness of quantile-based connectedness approaches in capturing risk spillovers in fintech and innovation-driven assets (Čech and Baruník 2017; Gabauer and Stenfors 2024). Moreover, the findings are in line with evidence reported by Ghaemi Asl et al. (2023), who document regime-sensitive interactions among financial technology indices, as well as by Ringstad and Tselika (2024) and Naeem et al. (2021), who show that sustainability-oriented assets exhibit asymmetric responses to market shocks. Within this context, the empirical evidence suggests that the ESG index tends to play a direction-setting role in information propagation during periods of adverse market conditions, indicating that ESG-related information may act as a reference point for investors when market uncertainty intensifies.

Overall, the analysis underscores that AI-ESG interactions are inherently dynamic and conditioned by prevailing market regimes, rather than being governed by stable or average relationships. The observed regime-dependent shifts in both the direction and intensity of information flow highlight the importance of accounting for distributional heterogeneity when assessing the linkage between technology-driven and sustainability-oriented assets.

6. Policy implications

The results indicate that information transmission in financial markets changes over time and across different market regimes. The finding that the ESG index assumes a more influential role in information flow during periods of heightened market stress suggests that ESG indicators may function as stabilizing components in portfolio diversification. From a policy perspective, this implies that sustainability-oriented market signals could be systematically integrated into macroprudential monitoring frameworks as complementary indicators of market-wide risk sensitivity. In this context, ESG-related measures may serve not only as long-term sustainability benchmarks but also as short-term signals reflecting shifts in market sentiment under stressed conditions.

Accordingly, incorporating ESG-based risk indicators into financial stability frameworks and developing stress-testing protocols that explicitly account for regime shifts may provide policymakers with significant advantages in the early detection of systemic vulnerabilities. Such an approach becomes particularly relevant in environments where technological innovation and AI-driven investment dynamics amplify cross-market information transmission. Embedding regime-sensitive indicators into stress-testing exercises may help policymakers better capture nonlinear spillover effects that intensify during extreme market states.

From the perspective of regulatory authorities, the development of policy tools that monitor potential excessive signal amplification arising from AI-driven dynamics and that support balanced information flows across financial markets may contribute to maintaining overall market stability. In particular, supervisory frameworks that jointly assess AI-driven market activity and sustainability-related signals may improve the oversight of emerging sources of systemic risk. These implications are especially relevant for institutions, financial regulators, and institutional investors concerned with systemic risk monitoring under technologically driven market dynamics. For institutional investors, incorporating regime-dependent ESG signals into portfolio risk management strategies may also enhance resilience against abrupt market transitions.

7. Limitations and future research

This study is limited to daily-frequency data covering the period from 1 November 2018 to 27 October 2025, and the AI-sustainability relationship is examined only through two global AI indicators (AI_NASDAQ and AIQ) and ESG index (MSCI World ESG Leaders). The restriction of the dataset to a specific set of indices and a relatively narrow time span constitutes the main limitations of the analysis.

In future research, the connectedness between AI and ESG could be examined using sectoral or regional classifications, and the analysis could also be extended to the individual subcomponents of ESG. Additionally, the application of comparative approaches that incorporate different market regimes, structural breaks, and time-varying dynamics may provide a more comprehensive understanding of the connectedness between AI and ESG. In addition, employing alternative definitions of AI and ESG indices may allow for testing the sensitivity of the findings to index selection. Moreover, the use of alternative data frequencies (e.g., weekly or higher-frequency observations) could help disentangle short- and long-horizon components of AI-ESG information transmission, thereby offering further insights into the temporal structure of regime-dependent connectedness.

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.

Acknowledgments

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

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Journal of Sustainable Digital Futures 2025 1(2)

Journal of Sustainable Digital Futures

journal homepage: https://jsdf.org.tr/

Asymmetric connectedness between Ethereum and sustainable digital assets: A Quantile-on-Quantile analysis

Burhan ERDOĞAN[1*], Gülhan DENİZ[2]

HIGHLIGHTS

[1] Sivas Cumhuriyet University, Yıldızeli Vocational School, Sivas, Türkiye, burhanerdogan@cumhuriyet.edu.tr
[2] Yozgat Bozok University, Akdağmadeni Vocational School, Yozgat, Türkiye, gulhan.deniz@bozok.edu.tr

ARTICLE INFO

Keywords:

Sustainability
Sustainable crypto assets
Ethereum
Quantiel-on-Quantile analysis

ABSTRACT

This study examines the dynamic connectedness between sustainable cryptocurrencies and Ethereum using the Quantile-on-Quantile Connectedness (QQC) methodology. The dataset consists of daily observations covering the period from April 19, 2019 to September 12, 2025. The analysis focuses on Cardano (ADA), IOTA, and Stellar (XLM), which are known for their high energy efficiency and environmentally sustainable blockchain architectures. Owing to its ability to measure the interactions between transmitting and receiving variables across different distributional quantiles, the QQC approach enables a detailed assessment of the direction and magnitude of information spillovers, particularly under extreme market conditions such as stress episodes or liquidity shortages. The findings indicate that Ethereum acts predominantly as a systemic net transmitter across most quantile levels, while Cardano and IOTA serve as net receivers, especially within medium and high quantiles. Stellar exhibits limited connectedness during low-volatility market regimes. Overall, the results suggest that the information transmission dynamics of sustainable crypto assets are highly sensitive to Ethereum's market influence, highlighting the increasing role of energy-efficient blockchain ecosystems in the broader digital finance landscape. The findings are important for portfolio managers in terms of making asset allocation decisions by taking into account the risk and diversification potential of sustainable cryptocurrencies relative to Ethereum.

1. Introduction

The theoretical linkage between sustainable (green) digital assets and conventional (dirty) digital assets primarily stems from structural differences in their market identities, perceived legitimacy, and risk-bearing characteristics. While conventional digital assets are largely associated with speculative price dynamics, high volatility, and short-term investment horizons, sustainable digital assets are positioned around environmental awareness, normative values, and long-term sustainability narratives. This differentiation establishes a theoretical foundation within the crypto ecosystem that allows for both synchronous interactions and conditional decoupling between the two asset classes (Haq and Bouri 2022; Sharif et al. 2023; Pham et al. 2022). From a theoretical standpoint, the relationship between green

[*] Corresponding author.

Received 21 November 2025; Received in revised from 23 December 2025; Accepted 28 December 2025
Available online 30 December 2025

and dirty digital assets exhibits an asymmetric and regime-dependent interaction structure. Conventional digital assets, owing to their deeper liquidity and broader investor base, tend to function as central hubs that absorb and transmit market shocks more rapidly. In contrast, sustainable digital assets are followed by a more selective investor base, leading to differentiated responses to information shocks. As a result, return and risk transmission often occurs in a unidirectional or quantile-sensitive manner rather than symmetrically (Naeem et al. 2023; Abdullah et al. 2025; Belguith et al. 2025).

From a behavioral finance perspective, the theoretical connection between the two asset classes is shaped by ethical perceptions, environmental awareness, and investor motivation. Sustainable digital assets are not perceived solely as financial instruments but also as representations of a normative and environmentally conscious stance, which directly influences investors’ risk tolerance, holding periods, and crisis-time portfolio adjustments. By contrast, conventional dirty digital assets are more closely associated with herd behavior, excessive price reactions, and speculative sentiment. This behavioral divergence provides a theoretical explanation for the persistent asymmetry observed in the interaction between the two asset groups, even during periods of market turmoil (Sharif et al. 2023; Umar et al. 2023; Vinogradova and Gubareva 2025). From a financial stability and systemic risk perspective, the linkage between sustainable and dirty digital assets can be interpreted through the redistribution of risk within the crypto ecosystem. Conventional digital assets frequently emerge as core transmitters of systemic risk, whereas sustainable digital assets, although not fully insulated from such risks, may assume receiver or partial buffering roles under specific market regimes. This indicates that the relationship between the two asset classes cannot be adequately captured by static correlations, but instead reflects a nonlinear and state-dependent interaction structure (Naeem et al. 2023; Chui et al. 2025; Deng et al. 2025).

Time and market-state dependence constitutes another fundamental dimension of the theoretical relationship between green and dirty digital assets. Under normal market conditions, interactions between these assets tend to remain relatively weak; however, during periods of heightened uncertainty and extreme market stress, the structure of connectedness can intensify or even reverse. Such tail-dependent behavior suggests that the links between sustainable digital assets and conventional cryptocurrencies are redefined during crisis episodes rather than remaining stable over time (Pham et al. 2022; Naeem et al. 2023; Alshammari et al. 2025). Finally, the theoretical relationship between sustainable green digital assets and conventional dirty digital assets should be evaluated within the broader context of the normative transformation of digital finance. By offering an alternative value system and ethical framework within crypto markets, green digital assets deepen intra-market segmentation, while their interaction with dirty digital assets becomes a key indicator of whether this transformation is temporary or structurally embedded. In this sense, the linkage between the two asset classes represents not merely a financial interaction but also a structural signal regarding the evolutionary trajectory of the digital asset ecosystem (Esmaeilian et al. 2024; Vinogradova and Gubareva 2025).

This study aims to examine the dynamic connectedness structure between sustainable cryptocurrencies, namely Cardano (ADA), IOTA (MIOTA), and Stellar (XLM), and Ethereum (ETH) by employing the Quantile-on-Quantile Connectedness (QQC) approach developed by Gabauer and Stenfors (2024). The analysis seeks to reveal the direction, magnitude, and tail risk dependence of information transmission among these assets across different time horizons and return quantiles representing varying market conditions, including low, medium, and high return regimes. Within this framework, the study empirically investigates whether Ethereum acts as a systemic information transmitter or receiver vis a vis sustainable digital assets, thereby providing deeper insights into the time and regime dependent nature of digital financial sustainability.

The main motivation of this study stems from the fact that the existing cryptocurrency literature has addressed the relationships between sustainable (green) crypto assets and conventional digital currencies in a rather limited and fragmented manner. Most prior studies either examine sustainable cryptocurrencies in isolation or evaluate them within an aggregated framework of the broader crypto market. In contrast, empirical research that directly and explicitly investigates the dynamic interaction between sustainable cryptocurrencies and dominant conventional digital currencies, particularly Ethereum, remains scarce. However, given its market depth, liquidity, and central role in information diffusion, Ethereum represents a natural benchmark and reference asset for understanding the behavior of sustainable digital assets. This study aims to fill this gap by analyzing the relationships between sustainable cryptocurrencies, namely Cardano, IOTA, and Stellar, and Ethereum within a QQC framework. In doing so, the study moves beyond the average-based or single-dimension connectedness approaches that dominate the existing literature. The quantile-on-quantile methodology allows for the simultaneous examination of the direction and intensity of information transmission across low, medium, and high return regimes, thereby enabling a more robust and clearer identification of nonlinear, asymmetric, and regime-dependent relationships between sustainable and conventional digital assets. As such, this study reveals dimensions of interaction that remain hidden under conventional mean-based analyses.

Another important contribution of this study lies in empirically assessing the systemic role of Ethereum vis-à-vis sustainable cryptocurrencies. Whether Ethereum functions as a dominant information transmitter or, under certain market conditions, assumes the role of an information receiver is a critical question for understanding the internal dynamics of the digital financial ecosystem. By demonstrating that this role may vary across time and return quantiles, the study challenges the notion of a static and unidirectional leadership structure within cryptocurrency markets. From an applied perspective, the findings offer important implications for investors and portfolio managers. Identifying how the relationship between sustainable cryptocurrencies and Ethereum evolves across different market regimes, particularly in extreme return conditions, provides valuable insights for risk management, portfolio diversification, and hedging strategies. Moreover, understanding the conditions under which sustainable digital assets decouple from or become more strongly connected with conventional cryptocurrencies contributes to a more informed interpretation of investor behavior in crypto markets. Finally, this study also provides meaningful insights for policymakers and regulatory authorities. In the context of digital financial sustainability, a key question concerns the extent to which sustainable crypto assets are integrated with or differentiated from the conventional cryptocurrency ecosystem. By revealing the regime-dependent nature of the relationships between sustainable cryptocurrencies and a central digital currency such as Ethereum, this study supports the development of more targeted and evidence-based regulatory and policy frameworks. In this sense, the study offers a comprehensive perspective that jointly informs academic debates and policy discussions on the sustainable transformation of digital finance.

The remainder of the paper is structured as follows. Section 2 offers an overview of the related literature. Section 3 introduces the dataset, variables, and econometric methods used. Section 4 discusses the results in light of the existing literature. The final section synthesizes the key findings of the study, discusses their policy implications, and outlines the main limitations alongside directions for future research.

2. Literature review

In recent years, the environmental impacts and sustainability dimensions of cryptocurrency markets have become a rapidly expanding area of research in the finance literature. While the environmental costs of energy-intensive conventional (dirty) cryptocurrencies have been widely debated, these criticisms have paved the way for the emergence and academic examination of "clean", "green", and "sustainable" digital assets. In this context, the literature comprehensively investigates the dynamic connectedness, spillover, and risk transmission mechanisms between green cryptocurrencies and dirty cryptocurrencies, energy markets, carbon markets, green bonds, ESG assets, and macro-financial indicators (Haq and Bouri 2022; Pham et al. 2022; Sharif et al. 2023; Siddique et al. 2023; Haq et al. 2023; Haq et al. 2023a).

The first major strand of the literature focuses on return and volatility connectedness between green and dirty cryptocurrencies. Studies employing dynamic connectedness, TVP-VAR, and frequency-based approaches document that green cryptocurrencies generally act as lower risk transmitters compared to dirty cryptocurrencies (Sharif et al. 2023; Naeem et al. 2023; Yildirim et al. 2025; Belguith et al. 2025). It is emphasized that this connectedness intensifies during periods of crisis and heightened uncertainty, whereas under normal market conditions green cryptocurrencies exhibit a more decoupled structure (Umar et al. 2023; Haq and Bouri 2022; Abdullah et al. 2025).

A second important stream of research examines the relationships between green cryptocurrencies and energy and fossil fuel markets. These studies show that fossil fuel price shocks affect green cryptocurrencies particularly in the medium and long run, while a stronger and more stable co-movement is observed with clean energy stocks and renewable energy assets (Umar et al. 2023a; Ali et al. 2024; Dias et al. 2023; Kaur et al. 2025; Pereira et al. 2025). Moreover, the connectedness between energy markets and green cryptocurrencies is shown to vary substantially across time, frequency, and quantiles (Naeem et al. 2023a; Deng et al. 2025).

Another prominent line of research investigates the interaction between green cryptocurrencies and carbon markets, carbon prices, and climate-related assets. The findings indicate that carbon price volatility and heightened climate risk awareness strengthen the correlation with green cryptocurrencies; however, this relationship is largely asymmetric and concentrated in extreme quantiles (Pham et al. 2022; Aloui et al. 2025; Abdullah et al. 2025). Within this framework, carbon-backed crypto assets and climate awareness indicators emerge as key determinants of the risk dynamics of green cryptocurrencies (Aloui et al. 2025; Fu et al. 2024).

The connectedness between green cryptocurrencies and green bonds, ESG indices, and sustainable financial instruments also occupies a central position in the literature. Studies reveal bidirectional but limited risk transmission between green cryptocurrencies and green bonds, while the diversification benefits with ESG assets become more pronounced during periods of market stress (Umar et al. 2023; Hassan et al. 2022; Mnif et al. 2025; Chui et al. 2025; Tabassum et al. 2024). In addition, the integration of Islamic crypto assets and halal financial instruments into sustainable crypto markets has emerged as a growing research area (Mnif et al. 2024; Tabassum et al. 2024).

Studies employing time-frequency and quantile-based methods clearly demonstrate that connectedness structures are highly sensitive to market conditions. In particular, during periods of downside risk, extreme quantiles, and heightened volatility, the risk transmission between green cryptocurrencies and other assets intensifies significantly (Naeem et al. 2023; Alshammari et al. 2025; Deng et al. 2025; Chui et al. 2025). By contrast, under normal market conditions, green cryptocurrencies tend to assume a more independent and diversification-enhancing role (Peng et al. 2024; Vinogradova and Gubareva 2025).

Studies focusing on media attention, environmental awareness, and cryptocurrency uncertainty indices emphasize the role of information flows in shaping green cryptocurrency dynamics. Increases in environmental media attention and climate awareness strengthen the decoupling of green cryptocurrencies from other financial assets, whereas periods of heightened cryptocurrency uncertainty intensify risk contagion between green and dirty cryptocurrencies (Ndubuisi and Urom 2023; Fu et al. 2024; Irani and Isayev 2025; Klayme and Gokmenoglu 2023).

From a portfolio management perspective, the majority of studies suggest that green cryptocurrencies can serve as diversification and hedging instruments under certain conditions. When evaluated alongside energy, carbon, commodity, and conventional cryptocurrency assets, green cryptocurrencies are shown to reduce portfolio risk; however, this contribution is time-varying and strongly dependent on frequency and market stress (Mnif et al. 2025; Attarzadeh et al. 2024; Kaur et al. 2025a; Naeem et al. 2023).

Finally, recent studies discuss whether green and sustainable crypto assets can be positioned as an independent asset class. The evidence suggests that these assets are still in an early stage of development; nevertheless, with the advancement of sustainable finance, climate policies, and digital transformation, green cryptocurrencies are expected to assume a more prominent role in the financial system over the long run (Esmaeilian et al. 2024; Vinogradova and Gubareva 2025; Yin et al. 2023; Alshammari et al. 2025a; Mnif et al. 2024a).

Collectively, these studies reinforce several overarching themes, indicating that interactions within sustainable digital asset markets are inherently asymmetric and strongly regime-dependent, with tail behaviour and extreme-quantile dynamics playing a central role in shaping return and volatility transmission mechanisms. In this strand of the literature, quantile-on-quantile and quantile-frequency methodologies have increasingly been preferred, as they are particularly effective in capturing nonlinear and state-dependent linkages that conventional mean-based approaches fail to detect. Moreover, sustainability-oriented digital assets exhibit behavioural patterns that are clearly distinct from those of traditional cryptocurrencies, especially during periods of heightened market stress and systemic crises. Despite these methodological and empirical advances, the existing literature remains limited in two important respects. First, there is a notable lack of studies that focus exclusively on sustainability-oriented cryptocurrencies and metaverse-associated green tokens within a QQC framework. Second, empirical evidence based on high-frequency datasets capable of jointly capturing short-run shocks and long-run regime shifts within sustainable digital ecosystems remains relatively scarce. Accordingly, the present study addresses these gaps by applying a QQC approach to high-frequency data in order to examine systemic risk and information-transmission dynamics within the sustainable crypto-metaverse nexus.

3. Data and methodology

3.1. Dataset and variables

This study aims to examine the return and volatility spillovers, shock transmission mechanisms, and time-varying connectedness dynamics between sustainable cryptocurrencies and Ethereum. The main objective of the analysis is to reveal how the interaction between these assets evolves not only under average market conditions but also across different time horizons and return levels. In this context, the study empirically assesses whether the relationships between sustainable cryptocurrencies and Ethereum are asymmetric, nonlinear, and sensitive to market conditions. The analysis is based on a daily dataset covering the period from 19 April 2019 to 12 September 2025. This period encompasses a broad time span that reflects different market conditions and structural transformations in cryptocurrency markets. The use of daily data allows for the simultaneous examination of short-term shocks and more persistent interaction effects. All price data employed in the study were obtained from the reliable data source Investing.com. The selected assets represent digital currencies that stand out for their relatively low energy consumption, innovative blockchain architectures, and long-term sustainability orientation. Accordingly, the analysis includes the series for Ethereum (ETH), Cardano (ADA), IOTA (MIOTA), and Stellar (XLM). These assets are classified as sustainable cryptocurrencies, as they employ energy-efficient blockchain protocols such as Proof-of-Stake (PoS) or Directed Acyclic Graph (DAG) structures.

Ethereum (ETH), Cardano (ADA), IOTA (MIOTA), and Stellar (XLM) are digital assets that stand out within the blockchain ecosystem in terms of their technological architectures, areas of application, and sustainability-oriented approaches. Ethereum is one of the most widely used platforms for smart contracts and decentralized applications, and its transition to a Proof-of-Stake-based consensus mechanism in 2022 significantly improved its energy efficiency. Cardano adopts an academically driven development approach and is built entirely on the Proof-of-Stake-based Ouroboros protocol, aiming to simultaneously achieve security, scalability, and sustainability. IOTA differs from traditional blockchains by relying on a Directed Acyclic Graph (DAG) architecture known as the Tangle; this mining-free structure enables energy-efficient and low-cost transactions, particularly for Internet of Things (IoT) applications. Stellar, on the other hand, is designed to facilitate cross-border payments and enhance financial inclusion, offering low transaction costs and fast validation times. Taken together, these four assets provide a comprehensive framework that encompasses Ethereum as a central actor with deep market integration, as well as alternative digital assets that differentiate themselves through sustainability, innovative architectures, and specialized use cases.

Ethereum's "Merge" update in 2022, which reduced its energy consumption by approximately 99%, Cardano's fully PoS-based consensus model, IOTA's mining-free DAG architecture, and Stellar's low energy requirements for transaction validation collectively reinforce the relevance of these assets for sustainability-focused analysis. These characteristics also make Ethereum a meaningful benchmark for examining its connectedness with other sustainable crypto assets.

To capture asymmetric and quantile-dependent relationships among variables, this study employs the Quantile-on-Quantile Connectedness (QQC) approach developed by Gabauer and Stenfors (2024). While conventional mean-based connectedness models mainly summarize average interactions under "normal" market conditions, the QQC framework explicitly reveals how these interactions vary across different segments of the distribution, such as low, medium, and high return or volatility regimes. The QQC approach adopts a two-dimensional structure that simultaneously measures both the intensity of shock transmission and the responsiveness of the receiving variable, thereby capturing information and volatility flows beyond a single average coefficient. This enables a more precise identification of whether the interactions between sustainable crypto assets and Ethereum strengthen in tail quantiles, under which conditions spillovers intensify, and in which regimes they weaken. In this respect, QQC provides a dynamic and tail-sensitive analytical framework that allows the connectedness between the sustainable crypto ecosystem and Ethereum to be examined beyond simple average effects.

3.2. Variable transformation

To ensure stationarity in the time series and facilitate interpretation of results in percentage terms, logarithmic differencing was applied to all variables. Accordingly, each transformed variable is defined as follows in Equation (1).

$$\Delta \ln X_t = \ln(X_t) - \ln(X_{t-1}) \tag{1}$$

Here, $\Delta \ln X_t$ denotes the logarithmic change in the corresponding series at time t. This transformation ensures variance stabilization while allowing increases or decreases in the variables to be evaluated in percentage terms.

3.3. Quantile VAR model

The econometric foundation of this study is based on the Quantile Vector Autoregression (QVAR) model. For multivariate time series $y_t \in \mathbb{R}^N$, the quantile-VAR model is defined as follows in Equation (2):

$$x_t = \mu(\tau) + \sum_{j=1}^{p} B_j(\tau) x_{t-j} + u_t(\tau) = \mu(\tau) + \sum_{i=0}^{\infty} A_j(\tau)\, u_{t-1}(\tau) \tag{2}$$

Here, $Q_{y_t}(\tau \mid F_{t-1})$ represents the conditional τ-quantile estimate of y_t; F_{t-1} denotes the information set available at time $t-1$; $\Phi_p(\tau)$ refers to the coefficient matrices specific to the quantile level; and $\varepsilon_t(\tau)$ denotes the error term. This structure allows modelling the heterogeneity in the response of variables to their past values across different quantile levels (for example, 0.1, 0.5, 0.9).

3.4. Generalized forecast error variance decomposition (GFEVD)

Using the QVAR model, the generalized forecast error variance decomposition, which measures the directional flow of information among variables, is computed as follows in Equation (3):

$$\tilde{\theta}_{ij}^{g}(\tau, h) = \frac{\sigma_{jj}^{-1} \sum_{k=0}^{h-1} (e_i' A_k(\tau) \Sigma e_j)^2}{\sum_{k=0}^{h-1} (e_i' A_k(\tau) \Sigma A_k(\tau)' e_i)} \tag{3}$$

In Equation (3), $\theta_{ij}^{g}(\tau, h)$ denotes the contribution of variable j to variable $i$at quantile level τ within the h-step-ahead forecast horizon. $A_k(\tau)$ represents the quantile-specific moving-average coefficient matrices; e_i and e_j are the selection vectors corresponding to the relevant variables in the system; and Σ denotes the error covariance matrix. This framework quantifies directional information flow by measuring the effects that variables exert on one another across different quantile levels.

3.5. Total connectedness index (TCI)

To determine whether each variable acts as a net transmitter or net receiver of information within the system, the directional net connectedness measure is defined as follows in Equations (4):

$$TCI(\tau) = \frac{\sum_{i \neq j} \theta_{ij}^{g}(\tau, h)}{\sum_{i,j} \theta_{ij}^{g}(\tau, h)} \times 100 \quad (4)$$

This index expresses, in percentage terms, the overall rate of interaction occurring among the variables in the system. A high TCI value indicates strong and widespread information transmission throughout the system, whereas a low value suggests that the variables behave more independently.

3.6. Directional net connectedness

To determine whether each variable acts as a net transmitter or net receiver of information within the system, the directional net connectedness measure is defined as follows in Equation (5):

$$NET_i(\tau) = \sum_{j \neq i} \theta_{ji}^{g}(\tau, h) - \sum_{j \neq i} \theta_{ij}^{g}(\tau, h) \quad (5)$$

If $NET_i(\tau) > 0$, the corresponding variable functions as a net transmitter of information within the system; if $NET_i(\tau) < 0$, it acts as a net receiver. This measure enables a quantitative assessment of each variable's directional interaction role across different quantile levels.

4. Empirical results

In this section, the dynamic relationships between the metaverse and sustainable crypto assets are analysed using the QQC approach. The analysis covers the period from 19 April 2019 to 12 September 2025 and is conducted using daily price returns. Unlike traditional mean-based methods, the QQC framework allows the examination of asymmetries, tail risks, and time-varying shock transmissions by uncovering the dynamics that change under different market conditions. The obtained results are first supported by descriptive statistics that reveal the distributional characteristics of the series, followed by the presentation of total, net, and directional connectedness analyses.

Table 1. Descriptive Statistics

	CARDANO	IOTA	XLM	ETHEREUM
Mean	-0.001	0	0	0.013
Variance	0.002	0.003	0.003	0.236
Skewness	-0.168***	0.203***	1.332***	40.087***
	(0.005)	(0.001)	(0.000)	(0.000)
Ex. Kurtosis	5.534***	10.741***	19.369***	1624.382***
	(0.000)	(0.000)	(0.000)	(0.000)
JB	2137.611***	8034.852***	26583.181***	183940710.108***
	(0.000)	(0.000)	(0.000)	(0.000)
ERS	-15.905***	-11.895***	-16.390***	-18.103***
	(0.000)	(0.000)	(0.000)	(0.000)
Q(10)	20.442***	19.758***	11.325**	0.784
	(0.000)	(0.000)	(0.037)	(0.997)
Q^2(10)	95.107***	43.560***	17.146***	0.003
	(0.000)	(0.000)	(0.002)	(1.000)

Note: *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively

Table 1 reports the key descriptive statistics for Cardano, IOTA, Stellar (XLM), and Ethereum. The mean and variance values indicate substantial differences across assets in terms of both levels and volatility. In particular, Ethereum's high variance reflects a more turbulent structure over the examined period. Significant deviations of skewness and kurtosis from zero demonstrate that the series exhibit asymmetric and fat-tailed distributions, while the Jarque-Bera test results confirm the rejection of the normality assumption. The ERS unit-root test verifies that the series are stationary, whereas the Q(10) and $Q^2(10)$ statistics point to the possibility of autocorrelation and volatility clustering. Overall, the descriptive statistics suggest that crypto asset markets exhibit high volatility and extreme-risk characteristics, indicating that a quantile-based modelling approach provides an appropriate analytical framework for these series.

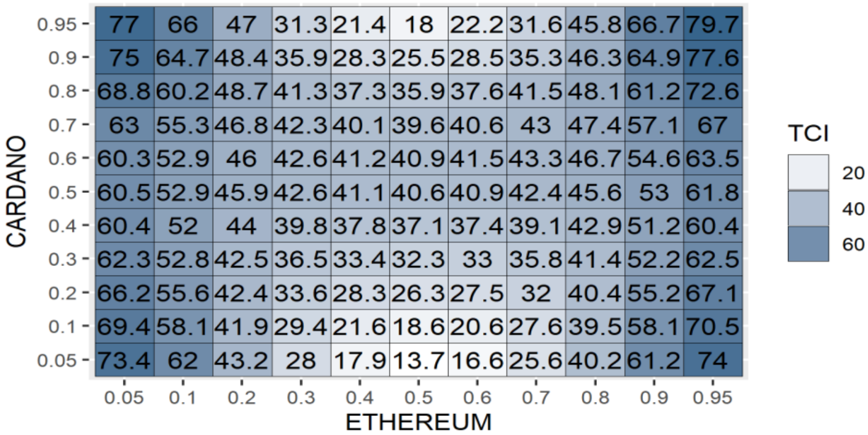

Figure 1. Quantile total connectedness indices for Ethereum and Cardano

Figure 1 illustrates the total connectedness between Ethereum and Cardano across various quantile combinations. The darker shades in the heatmap represent regions where information or volatility spillovers intensify at specific quantile pairings. The analysis indicates that TCI values increase notably in the tail quantile regions. This finding reveals that during periods of extreme upward or downward movements, the interaction between Ethereum and Cardano strengthens, meaning that market shocks propagate more intensely between these two assets. Conversely, the relatively lower TCI values observed in the mid-quantile regions suggest that under normal market conditions, the two assets exhibit partial decoupling. This result implies that portfolio diversification potential diminishes during periods of crisis and market stress, whereas Ethereum and Cardano tend to behave more independently when markets are calmer.

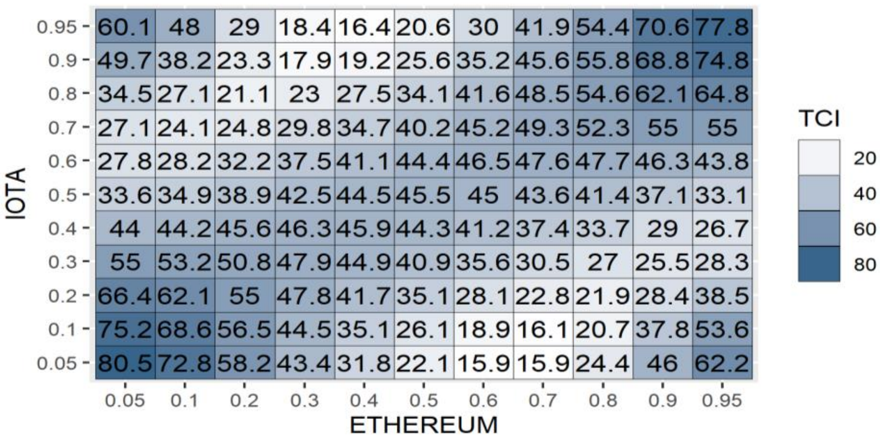

Figure 2. Quantile total connectedness indices for Ethereum and IOTA

Figure 2 presents the quantile total connectedness indices for Ethereum and IOTA. In the IOTA-Ethereum relationship, it is observed that TCI values are relatively high not only in the tail quantiles but also in the mid-quantile regions. This indicates that IOTA's market sensitivity is not limited to extreme price movements; even under more "normal" market conditions, it maintains a strong interaction with Ethereum. In other words, the IOTA-Ethereum linkage exhibits a more widespread and persistent connectedness structure. This result suggests that, due to IOTA’s integration with the metaverse ecosystem, it may respond early to trends originating in Ethereum. Consequently, holding these two assets together for diversification purposes may offer limited risk-reduction benefits.

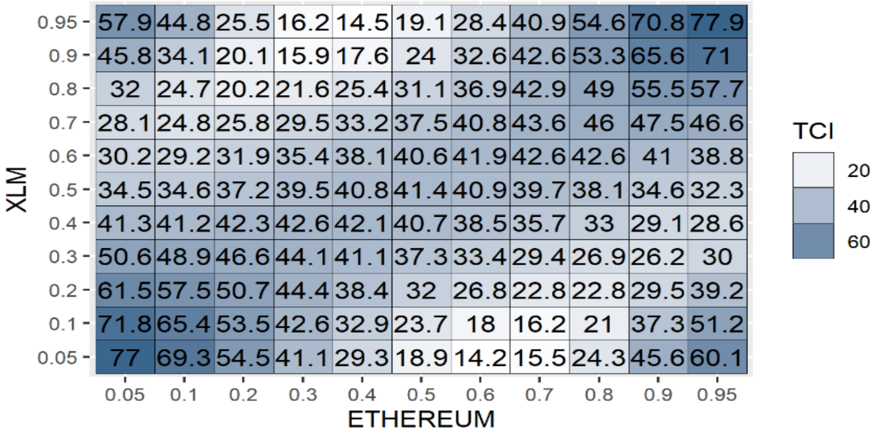

Figure 3. Quantile total connectedness indices for Ethereum and XLM

Figure 3 displays the quantile total connectedness indices structure between XLM and Ethereum. In the XLM panel, the TCI values exhibit a more dispersed and quantile-specific pattern. While the connectedness strengthens at certain quantile pairings, it weakens in others. This heterogeneous structure indicates that the interaction between XLM and Ethereum is highly dependent on specific market conditions and cannot be explained by a general correlation pattern. In this context, XLM may function at times as a risk-reducing asset in portfolios, while at other times it may act as a factor that accelerates shock transmission.

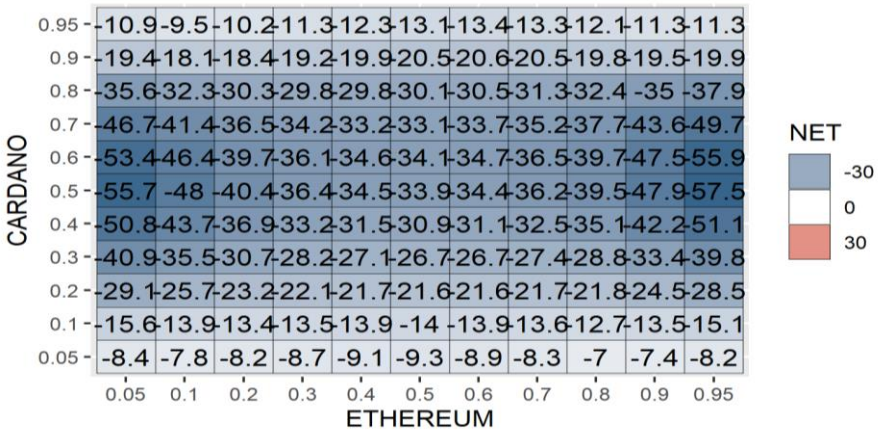

Figure 4. Net Quantile connectedness between Ethereum and Cardano

Figure 4 illustrates the direction of net quantile connectedness between Ethereum and Cardano. Negative shades indicate that Cardano is a net receiver of information, whereas positive shades signify that it acts as a net transmitter. The results reveal that negative tones dominate most of the matrix, indicating that Cardano generally functions as a net shock receiver. This finding supports the notion that Ethereum assumes a central role as a shock transmitter due to its market size, liquidity level, and ecosystem depth. This structure suggests that during periods of market turbulence, Cardano is more sensitive to movements originating from Ethereum; thus, news flows and price dynamics in Ethereum may exert persistent effects on Cardano.

Figure 5 presents the net connectedness structure for the IOTA-Ethereum relationship across various quantile combinations. Although IOTA appears as a net receiver in most quantile combinations, weak positive effects emerge in certain mid- and upper-quantile regions. This indicates that IOTA's influence on Ethereum increases—albeit modestly—under specific market conditions, suggesting periods of mutual interaction. However, the overall pattern clearly shows that IOTA is less central and more sensitive compared to Ethereum.

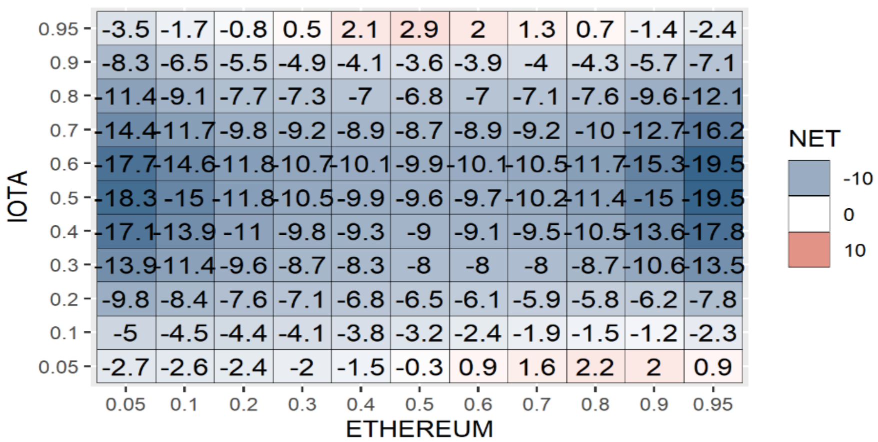

Figure 5. Net Quantile connectedness between Ethereum and IOTA

Figure 6 displays the net quantile connectedness structure between XLM and Ethereum. In the XLM panel, both positive and negative shades coexist, indicating that the directional relationship shifts across different quantile combinations. This finding suggests that XLM exhibits a bidirectional interaction pattern. In some periods, it receives shocks from Ethereum, while in others, it responds to the market with its own dynamics or partially transmits shocks outward. This bidirectional structure implies that XLM holds a more reactive and peripheral market position, yet it can gain strategic importance during certain periods.

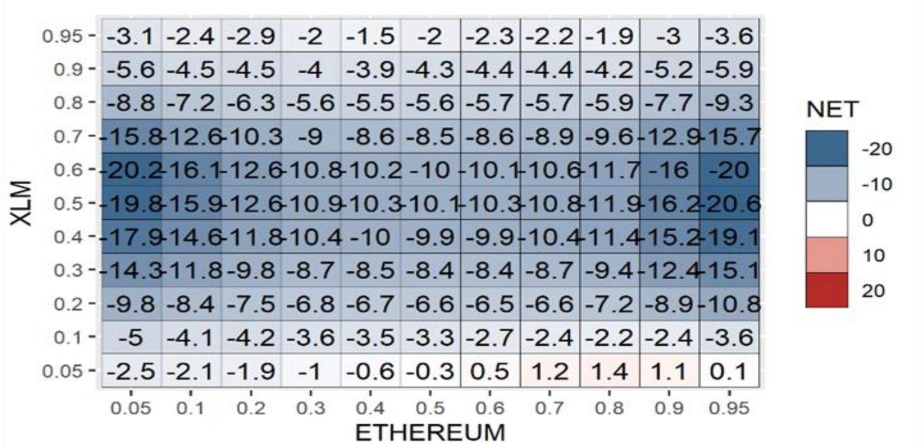

Figure 6. Net Quantile connectedness between Ethereum and XLM

Figure 7 illustrates the joint movement of the direct and reverse TCI indices for the Ethereum–Cardano pair over time. The results show that both indices rise notably during periods of market turbulence; however, during crisis episodes, the reverse TCI reaches relatively higher values. This finding indicates that reverse-quantile interactions become more dominant under extreme volatility conditions. In other words, during downturn scenarios, the flow of information from Cardano to Ethereum also increases, making the interaction bidirectional. Nevertheless, the long-term average suggests that Ethereum clearly maintains its dominant role.

Figure 8 shows the temporal evolution of the direct and reverse TCI indices between Ethereum and IOTA. Compared to the Cardano pair, the differences between the two indices appear narrower; however, in recent periods, the direct TCI displays an upward trend. This result suggests that in recent years, IOTA has developed a more autonomous price dynamic relative to Ethereum, partially reducing the bidirectional transmission of shocks. This pattern implies that IOTA may be moving toward greater independence, potentially due to technological advancements or an expansion of its application areas.

Figure 7. Direct and reverse total connectedness indices for Ethereum and Cardano

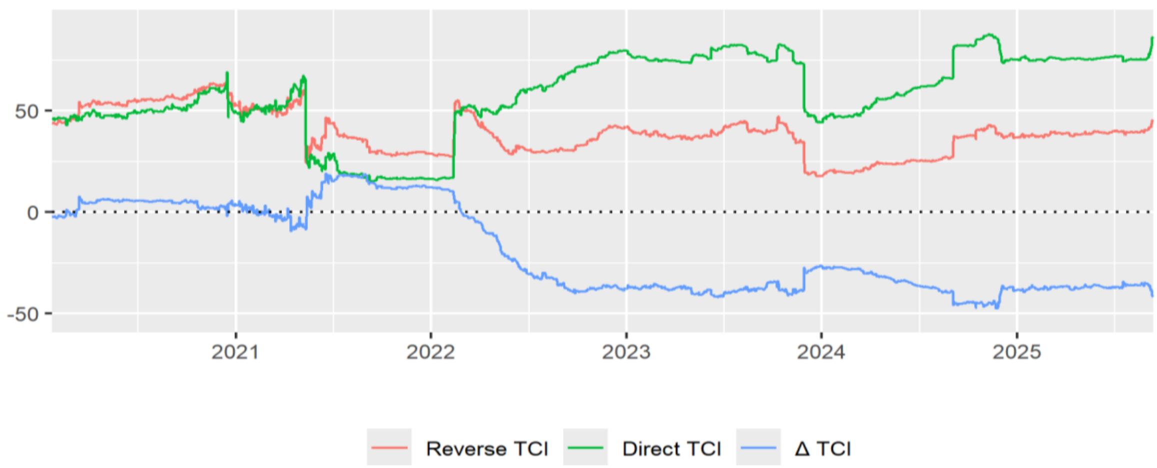

Figure 8. Direct and reverse total connectedness indices for Ethereum and IOTA

Figure 9. Direct and reverse total connectedness indices for Ethereum and XLM

Figure 9 presents the direct and reverse TCI indices for the XLM-Ethereum pair. The graph reveals periodic role shifts: in some periods, Ethereum-driven spillovers dominate, while in others, movements originating from XLM become more prominent. This fluctuating structure indicates that XLM's role in the market is sensitive to cyclical conditions and that there is no stable leader-follower relationship. Therefore, dynamic risk-management approaches should be preferred in portfolios that include XLM.

5. Conclusion and discussion

The findings of this study clearly demonstrate that the relationships between sustainable cryptocurrencies and conventional digital currencies exhibit a nonlinear, asymmetric, and market-regime-dependent structure. In particular, the pronounced increase in total connectedness (TCI) values between Ethereum and Cardano in the tail quantiles indicates that information and shock transmission intensifies during periods of heightened market stress. This result is consistent with prior studies emphasizing that interactions between green and conventional crypto assets strengthen during crisis periods (Pham et al. 2022; Sharif et al. 2023; Naeem et al. 2023). By contrast, the relatively lower connectedness observed in the middle quantiles suggests partial decoupling under normal market conditions, implying that sustainable cryptocurrencies may exhibit a degree of independence during calmer periods.

The results for the Ethereum-IOTA relationship partially diverge from several findings in the existing literature. In this study, TCI values remain high not only in the tail quantiles but also across the middle quantiles, indicating that the interaction between IOTA and Ethereum is persistent and widespread rather than being confined to extreme market conditions. This finding suggests that sustainable cryptocurrencies do not uniformly behave as crisis-sensitive assets and that certain tokens may remain strongly linked to the core of the conventional crypto market even under normal conditions. This outcome aligns with studies emphasizing the heterogeneous nature of sustainable digital assets (Haq and Bouri 2022; Vinogradova and Gubareva 2025). Moreover, IOTA's tendency to respond early to Ethereum-driven market signals supports the argument that green crypto assets may exhibit selective integration within the broader crypto ecosystem (Umar et al. 2023).

The results concerning the Ethereum-XLM relationship further reinforce the state-dependent and role-shifting perspective highlighted in the literature. Both total and net connectedness measures indicate that XLM alternates between acting as a shock receiver and, in some quantile combinations, a modest shock transmitter. This heterogeneous structure suggests that sustainable cryptocurrencies do not follow a uniform behavioral pattern and may attain systemic relevance under specific market conditions. These findings are consistent with earlier evidence showing that the role of green crypto assets varies across tail risks and quantiles (Naeem et al. 2023; Deng et al. 2025; Chui et al. 2025).

Net connectedness results indicate that Ethereum generally assumes a dominant role as an information transmitter. The fact that Cardano and IOTA appear as net receivers in most quantile combinations supports the literature emphasizing Ethereum's central position in the crypto ecosystem due to its market size, liquidity, and informational depth (Sharif et al. 2023; Abdullah et al. 2025). Nevertheless, the presence of weak positive net effects for IOTA and XLM in certain middle and upper quantiles suggests that sustainable cryptocurrencies are not entirely passive and can, under specific conditions, exert influence on Ethereum. This challenges the notion of a strictly unidirectional and static leader–follower structure in cryptocurrency markets.

The time-varying TCI results strongly confirm the phenomenon of intensified connectedness during crisis periods, as emphasized in the literature. For the Ethereum-Cardano pair, the rise in reverse TCI during turbulent episodes indicates that information flows become bidirectional under downside market conditions. This finding supports studies arguing that sustainable cryptocurrencies are not merely passive recipients of shocks but may engage in more complex interactions during periods of extreme volatility (Pham et al. 2022; Alshammari et al. 2025). At the same time, the persistence of Ethereum's dominance in the long-run average suggests that systemic hierarchy is weakened but not fully eliminated.

The temporal results for the Ethereum-IOTA and Ethereum-XLM pairs reveal that sustainable cryptocurrencies occupy an evolving market position over time. In particular, the recent increase in direct TCI for IOTA suggests that it has begun to develop a more autonomous price dynamic relative to Ethereum. Similarly, the periodic role reversals observed for XLM indicate a market position that is highly sensitive to cyclical conditions. These findings are consistent with recent literature emphasizing that sustainable cryptocurrencies exhibit dynamic and context-dependent roles rather than static market identities (Vinogradova and Gubareva 2025; Esmaeilian et al. 2024).

Overall, the findings of this study show that the relationships between sustainable cryptocurrencies and conventional digital currencies are quantile-, time-, and regime-dependent, thereby extending the existing literature beyond the insights offered by average-based approaches. By employing the QQC framework, this study explicitly uncovers tail risks, directional information transmission, and regime-specific dynamics that are often overlooked in conventional analyses. In this respect, the study provides a more nuanced and comprehensive understanding of the role of sustainable digital assets within the broader cryptocurrency ecosystem and makes a meaningful contribution to the existing literature.

6. Policy implications and recommendations

The findings of this study demonstrate that the interaction between sustainable cryptocurrencies and conventional digital currencies exhibits a time, quantile, and market regime dependent structure. This implies that policy frameworks targeting digital asset markets should move beyond uniform and static regulatory approaches and instead adopt flexible and condition-dependent designs. In particular, Ethereum's dominant role as an information transmitter vis-à-vis sustainable cryptocurrencies indicates that this asset should be treated as a special case within regulatory frameworks aimed at maintaining market stability. From the perspective of regulatory authorities, the intensification of linkages between sustainable cryptocurrencies and central digital currencies such as Ethereum during crisis periods suggests that channels of systemic risk transmission may be reconfigured through these assets. Accordingly, considering sustainable cryptocurrencies as fully insulated or inherently low risk instruments during periods of market stress may be misleading. Policymakers should therefore develop early-warning and monitoring mechanisms that explicitly account for tail risks and asymmetric information spillovers involving sustainable digital assets.

For investors and portfolio managers, the results indicate that sustainable cryptocurrencies should not be viewed unconditionally as safe-haven or hedging instruments. The strengthening of connectedness between Ethereum and sustainable cryptocurrencies in extreme quantiles and during periods of heightened market stress implies that portfolio diversification benefits may diminish precisely when they are most needed. Consequently, portfolio strategies should be designed not solely on average relationships, but rather on quantile- and regime-sensitive risk dynamics. From a financial stability perspective, the dynamic and time-varying positions of sustainable cryptocurrencies relative to Ethereum suggest that these assets can alternately function as passive shock receivers or, under certain conditions, as limited shock transmitters. This finding underscores that sustainable cryptocurrencies should not be treated as secondary or insignificant market participants within regulatory assessments. Instead, their potential to assume systemic relevance under specific market regimes should be explicitly recognized.

Moreover, the evolving market roles of sustainable digital assets imply that regulatory policies must be supported by continuous and adaptive updates. Evidence that assets such as IOTA and XLM can, at times, develop more autonomous price dynamics relative to Ethereum suggests that sustainable cryptocurrencies may gradually evolve into a more independent market segment. In this context, regulatory bodies should closely monitor technological developments and changes in market integration levels. Finally, in line with broader objectives of digital financial sustainability, policymakers should evaluate sustainable cryptocurrencies not merely as an environmental or ethical category, but within a framework that explicitly considers their market interactions and systemic risk channels. The findings derived from the QQC approach employed in this study demonstrate that such methodologies can contribute to more informed, targeted, and evidence-based policy design in digital asset markets. Accordingly, policies aimed at regulating sustainable cryptocurrencies should be developed with a forward-looking perspective that remains sensitive to evolving market conditions.

7. Limitations and future research

While this study provides important contributions by examining the dynamic connectedness structure between sustainable cryptocurrencies and conventional digital currencies within a Quantile on Quantile Connectedness framework, it is subject to several limitations. First, the analysis is restricted to sustainable cryptocurrencies represented by Cardano, IOTA, and Stellar, and to a single conventional digital currency, namely Ethereum. Although Ethereum's central role in the cryptocurrency market renders this choice methodologically justified, caution should be exercised when generalizing the findings to other major cryptocurrencies. Second, although the study employs high-frequency data, the sample period is limited to specific market conditions. Given the rapid structural transformation of cryptocurrency markets, future studies using longer time spans and covering alternative market regimes may provide deeper insights into the temporal evolution of connectedness dynamics. In this respect, extending the data horizon could enhance the robustness and generalizability of the results.

Another limitation relates to the methodological nature of the analysis. While the Quantile on Quantile Connectedness approach offers strong insights into the direction and intensity of information and shock transmission, it focuses on connectedness rather than causality. Accordingly, future research may complement these findings by employing quantile-based causality tests or dynamic structural models to allow for stronger causal interpretations. In addition, this study focuses primarily on market-based data and does not explicitly incorporate external factors such as investor behavior, regulatory developments, or technological innovations. Future research could enrich the analysis by integrating variables related to environmental awareness, media attention, or regulatory announcements in order to better understand the underlying mechanisms driving connectedness structures.

An important avenue for future research involves a more comprehensive examination of the internal interaction networks among sustainable cryptocurrencies themselves. In this study, each sustainable asset is analyzed only in a bilateral framework with Ethereum. However, employing multivariate and network-based models could reveal the systemic interdependencies among sustainable cryptocurrencies and provide a clearer picture of their collective role within the digital financial ecosystem. Finally, from a methodological perspective, although the Quantile on Quantile Connectedness approach constitutes a powerful analytical tool, combining it with wavelet-based or frequency-decomposed quantile methods may yield richer and more nuanced results. Therefore, future studies are encouraged to adopt multi-scale and hybrid methodological frameworks to further explore the complex dynamics of sustainable digital assets.

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.

Acknowledgments

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

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Journal of Sustainable Digital Futures 2025 1(2)

Journal of Sustainable Digital Futures

journal homepage: https://jsdf.org.tr/

The financial reflection of sustainability: A machine learning-based approach for BIST companies

Diler TÜRKOĞLU[1*], Serpil AYDIN[2]

HIGHLIGHTS

[1] Ardahan University, Faculty of Economics and Administrative Sciences, Ardahan, Türkiye, dilerturkoglu@ardahan.edu.tr
[2] Ondokuz Mayıs University, Faculty of Sciences, Samsun, Türkiye, serpil.gumustekin@omu.edu.tr

ARTICLE INFO

Keywords:

ESG
Firm performance
Machine learning
XGBoost model
Stakeholder theory
Financial development

ABSTRACT

Grounding the evaluation of Environmental, Social, and Governance (ESG) performance in Stakeholder Theory is increasingly vital, as sustainability practices strengthen firms' long-term value creation. Accordingly, this study examines the impact of ESG performance on key financial indicators for 50 firms listed on the Borsa Istanbul (BIST) Sustainability Index, with data continuity spanning the 2019-2020 period. The relationship between ESG scores and performance variables such as ROA, ROE, market capitalisation, financial leverage, net profit, EBIT, P/B ratio, current ratio, and Tobin's Q was analysed using the XGBoost algorithm to overcome the nonlinear limitations of traditional econometric models. The findings indicate that ESG practices have a more pronounced effect, particularly on market based indicators (e.g., Market Value and Tobin's Q). In contrast, their impact on accounting based indicators (e.g., ROA and ROE) remains more limited due to the complexity of internal operational transitions. By bridging the gap between machine learning and sustainability literature, this study provides a strategic roadmap for investors seeking to refine risk assessment through non-financial signals, for corporate managers aiming to boost market valuation via stakeholder-centric strategies, and for regulatory authorities in designing standardised ESG frameworks to enhance transparency and stability in emerging financial markets.

1. Introduction

In recent years, Environmental, Social, and Governance (ESG) issues have attracted significant attention from investors and researchers. ESG refers to a set of non-financial factors deemed essential for the long-term sustainability and value creation of businesses. These factors are critical in evaluating a company's overall performance. In the literature, the concept of ESG is categorised into three main components: the environmental dimension, the social dimension, and the governance dimension (De Masi et al. 2021; Fahrullah et al. 2024). ESG scores, utilised by investors and data providers to measure this performance, gauge the level of data disclosure regarding these areas and are customised for specific industrial sectors.

[*] Corresponding author.

Received 24 November 2025; Received in revised from 26 December 2025; Accepted 28 December 2025
Available online 30 December 2025

These ESG parameters, which are often perceived as technical measurement tools, are actually deeply rooted in the normative foundations of Stakeholder Theory, as proposed by Freeman (1994). Stakeholder Theory offers a comprehensive approach that integrates the technical aspects of business management with its ethical dimension, thereby opposing the "Separation Thesis," which argues that business and ethics are distinct domains. From this perspective, the value creation process cannot be defined solely by financial results; instead, it must be viewed as a multi-faceted process of compromise based on mutual obligations among all parties—investors, employees, customers, and society—interacting with the business (Freeman 1994). This theoretical framework suggests that a company's true success lies in satisfying all stakeholders, and that ESG activities can create synergy that is ultimately reflected in market performance.

Recent developments in the field of sustainability have necessitated the evaluation of companies not only by their financial results but also by their ESG performance. However, despite the growing importance of sustainability, empirical findings regarding the relationship between ESG and financial performance remain complex and occasionally contradictory. This leads to a critical research problem: traditional econometric models often fail to capture the high dimensional and nonlinear relationships inherent in ESG data, resulting in a gap in the literature regarding the precise predictive power of sustainability practices on different types of financial indicators. This methodological limitation creates strategic uncertainty for investors and highlights the necessity for a more robust, analytical approach.

Driven by this motivation and grounded in Stakeholder Theory, this study aims to fill this gap by analytically examining the effect of ESG scores on firm performance for 50 firms listed in the Borsa Istanbul (BIST) Sustainability Index between 2019 and 2020. The study formulates the research problem explicitly by differentiating between "market based " (e.g., Tobin's Q, Market Value) and "accounting based" (e.g., ROA, ROE) indicators to determine where ESG performance has the most significant impact. By utilising the XGBoost algorithm—an innovative machine learning model—this research seeks to overcome the linear constraints of previous studies and provide a more accurate guiding framework for investors.

The contribution of this study to the existing literature is twofold. First, it introduces a nonlinear methodological shift in the BIST context, demonstrating the superior predictive power of machine learning over traditional methods. Second, it provides empirical evidence that ESG performance is more strongly reflected in market based valuations—representing external stakeholder perceptions—than in internal accounting records, thereby offering a new theoretical and practical perspective on how sustainability value is priced in emerging markets. Following the literature review, the dataset and methodology are described, the variables used in the analysis are presented, and the findings are subsequently evaluated.

2. Literature review

Studies on the impact of ESG performance on financial indicators and the predictability of this relationship have seen a significant increase in recent years. However, the existing literature exhibits a high degree of fragmentation, with findings ranging from strong positive correlations to neutral or even adverse outcomes, often depending on the methodology and market context employed. These studies can generally be categorised into two main groups: those examining the ESG-financial performance relationship using traditional econometric methods and those testing predictive power using machine learning algorithms.

Within the first group, traditional empirical studies yield complex and occasionally contradictory results. For instance, Yavuz (2023) found a positive and significant relationship between total ESG scores and Return on Assets (ROA) in the context of the Borsa Istanbul. Similarly, Fahrullah et al. (2024) reported that ESG practices were positively associated with ROA in the Malaysian market. In contrast to these optimistic findings, some researchers argue that the relationship is strictly limited or sector specific. Şişman and Çankaya (2021) reported that ESG scores generally had no significant effect on financial performance in the airline sector. In contrast, Masongweni and Simo-Kengne (2024) highlighted a critical inconsistency, noting that while total ESG scores might be ineffective, specific sub dimensions, such as Social and Governance, can exhibit positive relationships. This heterogeneity is further supported by Parashar et al. (2024), who emphasised that firm level differences can render the ESG-ROE relationship insignificant.

From a theoretical standpoint, the divergence in findings is often interpreted through the lens of Stakeholder Theory. While traditional "shareholder centric" views might see ESG as an added cost, Wang (2024) and Nguyen et al. (2022) argue that meeting stakeholder expectations through ESG activities enhances corporate reputation and operational efficiency. A pivotal point of discussion in recent literature is the debate between the "agency problem" and "stakeholder management" approaches. Peng and Isa (2020) demonstrated that ESG activities do not generate agency costs; rather, they create consistent value. Furthermore, Habib et al. (2025) recently demonstrated that green financing acts as a moderator, suggesting that the ESG-performance link is not direct but influenced by financial structures.

The inconsistency of results in linear models has driven a methodological shift toward machine learning (ML) to decode nonlinear patterns. De Lucia et al. (2020) and Abdelfattah et al. (2025) found that ML models, particularly Random Forest, outperform traditional regression in predicting ROA and ROE across various countries. While some algorithms, such as XGBoost, have demonstrated high accuracy (91%) in specific markets, like China, the literature remains divided on the universal applicability of these findings. Dincă et al. (2025) provided a critical counter-narrative, arguing that high ESG scores do not necessarily increase financial prediction accuracy outside the service sector. Conversely, Sultana and Zeya (2025) used XGBoost to prove that ESG sentiment effectively reduces financial risk, highlighting that ML can capture qualitative nuances that traditional econometrics overlook.

Despite this growing body of work, a clear research gap remains. Most studies in the BIST context continue to rely on traditional linear models, which fail to account for the multidimensional and nonlinear interactions between ESG components and diverse financial metrics. Moreover, there is a lack of comparative analysis that distinguishes between the predictive power of ESG on market based versus accounting based indicators, using high performance ensemble algorithms such as XGBoost. This study aims to fill this gap by providing a comprehensive, nonlinear evaluation of BIST listed firms, moving beyond descriptive analysis to analytically demonstrate how market actors prioritise sustainability signals compared to internal financial reporting.

3. Data and methodology

This study covers the annual data of 50 firms listed on the Borsa Istanbul (BIST) Sustainability Index, with data continuity for the period from 2019 to 2020. The selection of this specific time period and sample is strategically determined by the availability of consistent ESG scores and financial data across the DataStream platform for BIST companies, ensuring a balanced panel that avoids survivorship bias. By focusing on the BIST Sustainability Index, the study ensures that the included firms are already committed to non-linear ESG disclosures, providing a robust basis for analysing the impact of these practices on financial performance.

The primary objective of this study is to investigate the impact of ESG scores on firm performance using the XGBoost (Extreme Gradient Boosting) algorithm. The selection of the dependent variables—ROA, ROE, Tobin's Q, Market Value, Financial Leverage, Net Profit, EBIT, and P/B Ratio—is rigorously grounded in the established literature on corporate finance and sustainability. Specifically, these metrics are chosen to provide a dual perspective: accounting based measures (ROA, ROE, Net Profit) reflect internal operational efficiency and historical performance, while market based measures (Tobin's Q, Market Value, P/B) capture external investor expectations and the pricing of sustainability signals. This comprehensive set of variables enables an analytical comparison of how ESG performance permeates various layers of financial reporting and valuation.

In this context, the dependent and independent variables used in the analysis process, along with their descriptive information, are presented in Table 1. The rationale for selecting the XGBoost algorithm over traditional linear methods or other machine learning models is based on several distinct advantages. Developed by Chen and Guestrin (2016), XGBoost is an ensemble learning method that carries out the prediction process through a combination of sequential decision trees. Unlike traditional multiple linear regression, which assumes a linear relationship and is sensitive to multicollinearity, XGBoost's tree based structure is inherently resistant to multicollinearity issues often found between ESG sub-components. Furthermore, XGBoost utilises gradient information and regularisation mechanisms (L1 and L2) to minimise loss functions while preventing overfitting, which significantly enhances the model's generalisation power compared to simpler models. Its ability to efficiently process high dimensional datasets and capture complex, nonlinear interactions makes it a superior tool for decoding the nuanced relationship between sustainability and firm performance.

Table 1. Variables used in the study

Variables	Abbreviation	Description
Dependent Variables		
Return on Assets	ROA	Net Income / Total Assets
Return on Equity	ROE	Net Income / Equity
Tobin's Q	TQ	(Market Value+Total Debt) / Total Assets
Market Value	MV	Share Price x Number of Shares
Financial Leverage	LEV	Total Debt / Total Assets
Net Profit	NETPRO	Net Income / Net Sales
Earnings Before Interest and Taxes	EBIT	Net Income + Interest Expenses + Tax Expenses
Market-to-Book Ratio	P / B	Market Value / Equity
Control Variable		
Current Ratio	CR	Current Assets/Current Liabilities
Independent Variables		
ESG Score	ESG	Environmental + social + Governance
Environmental Score	E	Environmental Pillar score
Social Score	S	Social Pillar Score
Governance Score	G	Governance Pillar Score

The ratios utilised to determine firm performance were selected based on the relevant literature (Velte 2017; Konak and Çıtak 2018; Gregory 2021; Konak and Türkoğlu 2022; Bui et al. 2023; Yenisu and Türkoğlu 2023; Zulnisyam et al. 2025). Financial performance valuation frequently employs metrics such as Market Value, Financial Leverage, Net Profit, Earnings Before Interest and Taxes (EBIT), tree based (P/B), Current Ratio (CR), and Tobin's Q. These metrics provide significant outputs regarding both accounting based and market based firm performance (Mahfirah et al. 2025).

In this regard, Return on Assets (ROA) is used to measure the firm's general operational efficiency level as it reflects the ability to generate income through all its assets (Jonnius and Marsudi 2021). Indicating the effectiveness of economic resources allocated to the business, ROA is calculated by dividing net income by the total assets used in the business during the reporting period (Al-Sa 2018). Another variable, Return on Equity (ROE), is calculated by dividing net income after taxes by average equity. This critical measure reveals the profit generated for each unit of equity after taxes are taken into account. Furthermore, ROE is a reflection of the operational status of the business and the efficiency with which invested capital is managed; a higher ROE indicates increased profitability and substantial business value (Ebaid 2009; Yang et al. 2010; Bui et al. 2023).

Tobin's Q, used as a measure of firm value, is obtained by dividing the sum of market value, total liabilities, preferred stock, and minority interest by total assets (Panaretou 2014; Wong et al. 2021). In evaluation, a value lower than 1 implies that the market values the firm lower than the sum of its assets. In contrast, a value higher than 1 indicates that the firm's market value exceeds the sum of its assets due to unrecorded factors such as brand equity (Butt et al. 2023).

Regarding other financial indicators: Market Value refers to the product of share price and total number of outstanding shares; Financial Leverage is the ratio of total debt to total assets; Net Profit (Margin) is the ratio of net profit to net sales; EBIT is the sum of net profit, interest expenses, and tax expenses; P/B Ratio is the ratio of the company's market capitalization to equity; and Current Ratio (CR), included as a control variable, expresses the ratio of current assets to current liabilities.

The descriptions and formulas for the performance metrics (Root Mean Square Error) RMSE and Mean Squared Error (MSE) used to evaluate the results of the XGBoost algorithm applied within the scope of these variables are presented in Table 2 (Saloo et al. 2024).

Table 2. Performance Measurement Metrics of Developed Models

Performance Criteria	Definition	Formula
Root Mean Square Error (RMSE)	It is a metric indicating the magnitude of error. A lower RMSE indicates that the model's predictions are closer to the actual data.	$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}$
Mean Squared Error (MSE)	It penalizes large errors by taking the average of squared errors; thus, a lower MSE is considered to indicate a better model.	$MSE = \frac{1}{n}\sqrt{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}$

3.1. XGBoost model

Developed by Chen and Guestrin (2016), XGBoost (eXtreme Gradient Boosting) is a method employing an ensemble learning approach, carrying out the prediction process through a combination of sequential models composed of decision trees. The algorithm utilises gradient information to minimise the loss function and also leverages the second derivatives (Hessian) of the loss function to optimise the model more precisely. Furthermore, it incorporates regularisation mechanisms to limit the problem of overfitting. These features enhance both the generalisation power and the prediction performance of XGBoost. The method has gained wide acceptance in the literature due to its ability to process high dimensional datasets efficiently and its relatively fast interpretation (Sarker 2021).

The objective function and the regularization term of the XGBoost algorithm are generally formulated as follows in Equation (1) (Oukhouya et al. 2024):

$$L = (\phi) = \sum_{i} l\big((y_i, \hat{y}_i)\big) + \sum_{k} \Omega(f_k) \tag{1}$$

Here, the regularisation term Ω is expressed as:

$$\Omega(f) = \gamma T + \frac{1}{2}\lambda\|\omega\|^2 \tag{2}$$

In this Equation (2) l represents the differentiable convex loss function, T denotes the number of leaf nodes in the tree, ω represents the score vector (weights) in the leaf nodes, γ is the complexity penalty parameter associated with the number of leaf nodes, λ denotes the regularisation parameter.

4. Empirical results

The impact of ESG scores on firm performance was analysed using the XGBoost algorithm on a dataset of 50 BIST Sustainability Index firms. Prior to analysis, data were normalised, and hyperparameters were optimised using the GridSearchCV method to ensure model robustness.

4.1. Descriptive statistics and correlation analysis

As shown in Table 3, the average ESG performance of the sampled firms is 72.03. Detailed sub-component analysis reveals that firms achieve their highest performance in the Social dimension (Mean: 78.83) and their lowest in Governance (Mean: 62.71). Regarding financial metrics, the ROE exhibits higher average values (22.41%) compared to the ROA (12.22%), although significant heterogeneity is evident, as indicated by the high standard deviations.

The correlation heatmap (Figure 1) provides critical preliminary evidence: while total ESG scores correlate highly with their sub-components, their interaction with financial indicators varies significantly. Specifically, ESG components show stronger visual associations with Market Value (MV) and EBIT compared to ratio-based indicators like ROA or Tobin's Q. This suggests that ESG signals may have a more immediate reflection on market based metrics than on internal accounting profitability.

In this study, the impact of ESG scores on firm performance was analysed using the XGBoost algorithm, which utilised 6 years of data from 50 firms listed in the BIST Sustainability Index for the period from 2019 to 2020. To prevent data leakage, the data were first sorted chronologically. Subsequently, the data were normalised to avoid biases arising from scaling discrepancies. To maximise the model's prediction accuracy, hyperparameter optimisation was performed using the GridSearchCV method. Following the pre-processing steps, the dataset was split into 70% training and 30% testing sets. Descriptive statistics regarding the variables used in the analysis are presented in Table 3.

Table 3. Descriptive statistics

Variables	N	Mean	Std.Dev.	Min	25%(Q1)	Median	75%(Q3)	Max
TQ	300	0.3206	0.1789	0.0031	0.1712	0.3122	0.4376	0.9039
ROA	300	12.2281	11.2757	-17.6900	6.1400	10.0100	16.4900	93.7900
ROE	300	22.4137	48.4935	-349.1000	8.4100	19.5750	39.7750	242.5600
MV	300	9.8044	1.4542	6.3319	8.7637	9.8947	10.7521	13.0785
FKAL	300	0.3190	0.1798	0.0016	0.1704	0.3112	0.4371	0.9037
ESG	300	72.0312	14.0749	16.0200	64.7850	74.4650	82.0125	94.9800
E	300	71.5387	19.1112	3.4500	62.3375	72.3900	86.1300	99.1300
S	300	78.8312	16.0579	15.4300	70.8100	83.5400	91.3675	97.4000
G	300	62.7110	17.3348	9.0500	52.3750	63.4650	75.8400	94.3100
NETPRO	300	9.5306	17.7234	-94.5300	2.9225	7.9900	13.6675	160.6100
EBIT	300	9,650,724	20,541,540	-6,957,011	801,033	3,268,784	8,792,180	178,861,000
PB	300	2.3877	18.2418	-210.9200	1.0000	1.5050	2.5650	227.9700
CR	300	1.2768	0.6334	0.3100	0.8900	1.1400	1.4225	5.3800

Upon examining the descriptive statistics presented in Table 3, it is observed that the average ESG performance of the firms is 72.03. When the sub-components are detailed, it is noteworthy that firms exhibit the highest performance in the Social (S) dimension (Mean: 78.83), followed by the Environmental (E) dimension (Mean: 71.53). In contrast, the lowest performance occurs in the Governance (G) dimension (Mean: 62.71).

Regarding financial indicators, Return on Equity (ROE) follows a higher trend with an average of 22.41% compared to Return on Assets (ROA) (12.22%). However, the high standard deviation values in the ROE and P/B variables, along with the wide range between the minimum and maximum values (especially the variation in ROE, which ranges from -349.10 to 242.56), indicate significant heterogeneity among the sampled firms in terms of financial structure and profitability. The fact that the Tobin's Q (TQ) average is 0.32 may imply that firms' market values are priced below their replacement costs. The Current Ratio (CR), included as a control variable, has an average of 1.27, indicating that the firms' short-term debt repayment capabilities are generally at a reasonable level.

Figure 1 shows the correlation heatmap provides a visualisation of the direction and strength of the relationships between ESG components and firm performance variables. The colour distributions and patterns of the matrix clearly reveal the intensity of relationships between variable sets. Upon examining the heatmap, the most prominent finding is the expected high positive correlation (bright yellow areas) between the total ESG score and its sub-components (Environmental, Social, Governance). However, a more critical finding regarding the study's focus is the interaction between ESG scores and financial indicators. The visual indicates that lighter colour tones (orange/red) dominate the intersection points of ESG and its sub-components with Market Value (MV) and EBIT variables; conversely, the relationship with ratio-based indicators such as ROA, ROE, and Tobin's Q (TQ) remains weaker (dark purple).

This visual evidence supports the thesis, which will be detailed in the analysis section, that ESG practices have a more pronounced reflection on firms' market value (MV) compared to accounting profitability (ROA/ROE). Furthermore, while the high correlation (multicollinearity) between ESG sub-components could lead to biases in traditional models such as linear regression, the XGBoost algorithm preferred in this study allows for more reliable predictions by exhibiting resistance to such multicollinearity issues thanks to its tree based structure.

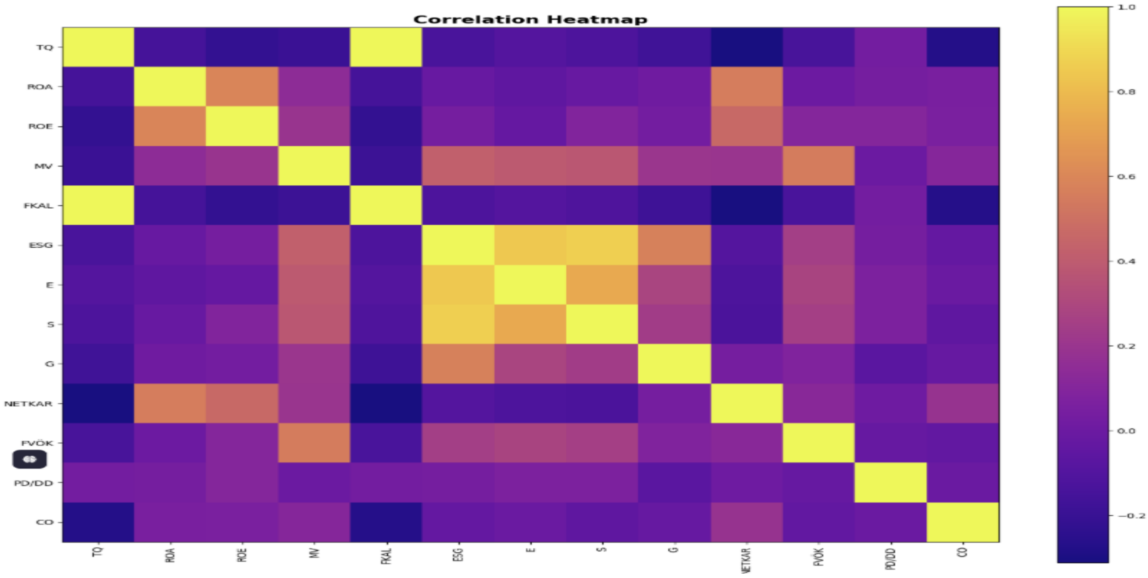

Figure 1. Correlation heatmap between variables

4.2. XGBoost prediction results

The models were trained using extended feature sets that included lagged variables, firm fixed effects, scale transformations, and ESG components. For each dependent variable, model success was evaluated using R^2, MSE, and RMSE metrics, and optimal hyperparameters determined via GridSearchCV were reported (Table 4).

Table 4. Analysis findings and best hyperparameters

Dependent Variables	R^2	MSE	RMSE	Best Hyperparameters
TQ	0.7630	0.003375	0.0581	colsample_bytree=0.8, learning_rate=0.05, max_depth=3, n_estimators=400, subsample=0.8
ROA	0.4194	55.1672	7.4275	colsample_bytree=0.8, learning_rate=0.05, max_depth=5, n_estimators=400, subsample=0.8
ROE	0.1345	1549.9335	39.3692	colsample_bytree=0.8, learning_rate=0.05, max_depth=3, n_estimators=400, subsample=0.8
MV	0.9982	0.003685	0.0607	colsample_bytree=1.0, learning_rate=0.05, max_depth=5, n_estimators=400, subsample=1.0
FKAL	0.7763	0.005738	0.0757	colsample_bytree=0.8, learning_rate=0.05, max_depth=3, n_estimators=400, subsample=0.8
NETPRO	0.1988	137.1071	11.7093	colsample_bytree=0.8, learning_rate=0.01, max_depth=5, n_estimators=200, subsample=0.8
EBIT	0.8228	0.4693	0.6851	colsample_bytree=1.0, learning_rate=0.05, max_depth=3, n_estimators=400, subsample=0.8
PB	0.6246	0.1037	0.3220	colsample_bytree=0.8, learning_rate=0.01, max_depth=3, n_estimators=400, subsample=0.8

Upon examining Table 4, the high R^2 values obtained, particularly for MV (0.9982) and EBIT (0.8228), are noteworthy. In machine learning models, such high explanatory power often raises concerns regarding the risk of "overfitting". However, the fact that model performance in this study is reported on the test set rather than the training data, and that hyperparameters were determined under cross-validation using GridSearchCV, indicates that this result stems from the strong autoregressive structure of the relevant variables (the power of past data to explain the present) rather than model memorisation.

Evaluating the findings by variable, it is observed that the Market Value (MV) model achieved almost perfect explanatory power. The inclusion of lagged variables and firm fixed effects allowed the model to capture the structural dynamics of market value. This confirms the theoretical expectation that market value is highly dependent on past information and historical trends. Similarly, the Tobin Q (TQ) model ($R^2 = 0.763$) provided high accuracy. The use of ESG components alongside lagged financial indicators enabled a robust prediction of the market to book ratio, supporting the view that TQ is a market based metric reflecting ESG sensitivity.

Conversely, more limited results were obtained for accounting based indicators. While a moderate explanatory power ($R^2 = 0.419$) was observed for Return on Assets (ROA), it is understood that operational efficiency is more closely related to internal cost structures and management decisions than to ESG. The Return on Equity (ROE) and Net Profit (NETPRO) models exhibited the lowest performance ($R^2 < 0.20$). The high volatility of ROE and Net Profit items, along with their excessive susceptibility to periodic shocks and accounting policies, makes it difficult to predict these variables using external factors and ESG scores.

In conclusion, the findings reveal that market based performance indicators (MV, TQ, EBIT, LEV) can be predicted with high accuracy using machine learning models. In contrast, the predictability of accounting based metrics (ROA, ROE, NETPRO) remains more limited. This divergence is consistent with views in the literature suggesting that the impact of ESG is concentrated on investor perception and market valuation rather than financial statements.

5. Discussion

The empirical findings of this study offer significant theoretical, methodological, and inferential implications for the sustainability literature. The high predictive accuracy of ESG scores regarding market based variables (MV, TQ, and EBIT) provides strong empirical support for Stakeholder Theory. The superior performance of market based models suggests that external stakeholders and investors perceive ESG performance as a critical indicator of long term value creation. This aligns with the findings of Nguyen et al. (2022), who observed that ESG impacts on Tobin's Q are significantly higher than those on ROA or ROE in the S&P 500. Our results confirm this trend in an emerging market context (BIST), reinforcing the "Stakeholder-Oriented" view that ethical and transparent practices make firms more attractive to investors, thereby rapidly increasing market valuation. Conversely, the limited predictability of accounting based metrics (ROA, ROE) suggests that the transition from sustainability practices to internal operational profitability is a more complex and long-term process. This finding is consistent with Yavuz (2023) and Liu and Fill (2025), who argued that ESG's primary impact is on market perception rather than immediate financial statements.

The inferential implication here is that while ESG may not yield short-term accounting profits, it serves as a robust signal of financial resilience and lower risk, as supported by Sultana and Zeya (2025). From a methodological perspective, the success of the XGBoost algorithm in this study demonstrates the necessity of utilising nonlinear models to decode ESG data. Traditional linear regressions often suffer from multicollinearity between ESG sub-dimensions; however, XGBoost's tree based structure effectively manages these dependencies, providing more reliable predictions. The high R^2 values for Market Value and EBIT are attributed to the model's ability to capture the strong autoregressive structure and firm-specific fixed effects. This implies that current financial performance is deeply rooted in historical trends and structural characteristics, which, when combined with current ESG signals, provide a robust framework for forecasting future performance. These results challenge the critical view of Dincă et al. (2025) by demonstrating that, in the BIST context, ESG scores indeed significantly enhance the accuracy of financial forecasts when modelled using advanced machine learning techniques.

6. Policy implications and future research

The findings of this study offer concrete and actionable insights for regulatory authorities, corporate decision-makers, and market participants, while also identifying the boundaries of the current research and directions for future inquiry.

6.1. Policy implications

For policymakers and regulatory authorities, the high predictive power of ESG signals on market valuation underscores the need for a more structured and transparent sustainability ecosystem. It is recommended that authorities, such as the Capital Markets Board of Turkey (SPK), work toward standardising sustainability reporting practices to eliminate information asymmetry. Uniform reporting standards would allow investors to access comparable data, leading to more efficient pricing of sustainability performance in the BIST. To promote the broader adoption of ESG practices, governments should expand tax advantages, green financing instruments, and credit support. Lowering the cost of capital for high-performing ESG firms would alleviate the initial cost burden of sustainability investments and encourage long-term commitment. For corporate decision-makers and managers, the study demonstrates that ESG is not merely an ethical choice but a strategic tool for value creation. Since the findings reveal that ESG practices have a pronounced effect on market based indicators, managers should treat sustainability disclosures as a primary signalling mechanism to attract long-term institutional investors. Incorporating ESG into the core business strategy can serve as a buffer against market shocks, enhancing financial resilience and reducing perceived risk among external stakeholders.

6.2. Limitations and future research

Despite its contributions, this study has several limitations that should be acknowledged. The analysis is limited to 50 firms in the BIST Sustainability Index, for which data continuity is available for the 2019-2020 period. This narrow timeframe may not fully capture the long-term, multi-year lags between ESG investments and their eventual reflection on internal accounting profitability (ROA/ROE). While XGBoost provided superior predictive power, the study primarily focuses on numerical financial data and does not incorporate qualitative factors such as ESG sentiment or text-based disclosures. Future studies could compare machine learning models, such as XGBoost, with deep learning architectures, like LSTM or CNN, to determine if these techniques offer even higher accuracy in forecasting financial trends. Expanding the dataset to cover a longer time series (e.g., 10 years) would help reveal the long-term "pay-off" period of sustainability practices on accounting based performance metrics.

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.

Acknowledgments

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

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Journal of Sustainable Digital Futures 2025 1(2)

Journal of Sustainable Digital Futures

journal homepage: https://jsdf.org.tr/

Sustainability performance of countries in the context of the sustainability uncertainty index and ESG indicators: An integrated CRITIC-EDAS approach

Abdülkadir ALICI[1*], Yahya SÖNMEZ[2], Sevim YILMAZ[3]

HIGHLIGHTS

[1] Kastamonu University, School of Civil Aviation, Kastamonu, Türkiye, aalici@kastamonu.edu.tr
[2] Kastamonu University, Daday Nafi and Umut Çeri Vocational School, Kastamonu, Türkiye, yhysnmz@yahoo.com
[3] Kastamonu University, School of Civil Aviation, Kastamonu, Türkiye, sevimyilmaz@kastamonu.edu.tr

ARTICLE INFO

Keywords:

Sustainability
Sustainability uncertainty index
ESG
MCDM
Environmental sustainability

ABSTRACT

This study aims to evaluate the sustainability performance of countries within a multidimensional framework, considering not only environmental and social outcomes but also the level of uncertainty related to sustainability policies. To this end, ESG-based Sustainability Uncertainty Index (SUI/ESGUI), per capita CO_2 emissions, Gini coefficient, renewable energy consumption (API), Environmental Performance Index (EPI), Sustainable Development Score (SDG), Human Development Index (HDI) and Rule of Law Index (WGI) data for 25 countries for the year 2023 were used. The criteria weights in the study were determined using CRITIC, an objective method based on the information content of the dataset; subsequently, the countries' relative sustainability performances were ranked using the EDAS method. Research findings reveal that the most decisive factors in distinguishing sustainability performance are the Rule of Law and Sustainability Uncertainty; Sweden leads with low uncertainty and high ESG performance, while Russia, China, and the US, which struggle with high emissions and policy uncertainty, are at the bottom of the list; This situation demonstrates that environmental improvements alone are not sufficient to achieve sustainable development goals; improving institutional quality and reducing policy uncertainty are also critical.

1. Introduction

The study examines different approaches to assessing countries' sustainability performance based on the SUI and ESG indicators. Country sustainability will be addressed from a multifaceted perspective, not only based on existing measurement methods and indicators but also by considering the uncertainty associated with sustainability. This will provide a more comprehensive discussion of the existing academic and methodological framework for measuring sustainability.

Today, the global climate crisis has evolved beyond being merely an environmental problem and has become a multifaceted threat, intertwined with social inequalities, democratic regression, the feasibility of achieving sustainable development goals, and the impact of international regulations, such as the Paris Agreement. Therefore, measuring countries' sustainability performance should extend beyond

* Corresponding author.

Received 30 September 2025; Received in revised from 17 December 2025; Accepted 28 December 2025
Available online 30 December 2025

environmental indicators to include social and governance elements, such as social justice, human development, institutional capacity, and income distribution. Given the interconnected and interdisciplinary nature of sustainability, this holistic approach is crucial for understanding the impacts on countries' well-being.

Recent academic studies have revealed that the dynamic interaction between the climate crisis, inequality, and sustainability is becoming increasingly apparent. The literature emphasizes that the impacts of the climate crisis are not reflected equally across all segments of society, and that disadvantaged groups (women, children, the elderly, people with disabilities, and low-income populations) are disproportionately affected by this process. Çolakoğlu (2023) study also highlights this situation, revealing that these groups, which contribute least to climate change, are exposed to the greatest negative impacts, and that children, in particular, are the most vulnerable to the adverse effects of the climate crisis. This clearly demonstrates that social justice and human rights-based indicators cannot be ignored in the assessment of sustainability performance.

Multidimensional issues such as sustainable development, environmental quality, human development, governance capacity and income inequality occupy a central place in today's global policy agenda; there is an increasing need for indices that can measure the economic, social and institutional performance of countries in a comparable manner to monitor progress in these areas (UNDP 2024). In this context, the SDG Index, which tracks holistic progress towards sustainable development goals; the EPI, which assesses environmental performance across dimensions of air quality, climate, biodiversity, and resource management; the HDI, which combines life expectancy, education, and income; the WGI, which cover dimensions such as the rule of law, control of corruption, and democratic accountability; the Gini coefficient, which measures income inequality; and data sets on production-related CO_2 emissions stand out as key indicators that enable multidimensional analyses of countries' sustainability and development performance (Wolf et al. 2022; Kaufmann et al. 2010; World Bank 2024b; Friedlingstein et al. 2025). However, each of these indicators ranks countries along a specific dimension; therefore, they do not provide a holistic measurement framework encompassing all elements of sustainability. Each index prioritizes its own focus, making comprehensive sustainability analysis difficult.

On the other hand, sustainability is a multifaceted concept that requires the simultaneous consideration of economic growth, environmental protection, and social well-being (UN 2015). Therefore, the applicability and effectiveness of sustainability policies are closely related not only to their content but also to the level of uncertainty surrounding these policies (Baker et al. 2016). In recent years, the impact of uncertainty regarding sustainability policies on investment decisions, market expectations, and perceptions of country risk has been increasingly discussed (Hu et al. 2023; Liang et al. 2022; Wang et al. 2023). The SUI, developed in this context, is a crucial tool that facilitates the systematic monitoring of the level of uncertainty surrounding sustainability policies in countries (Ongan et al. 2025).

This study aims to analyze countries using a CRITIC-EDAS-based Multi-Criteria Decision-Making (MCDM) approach, combining indicators such as SUI, CO_2 emissions, the Gini coefficient, API, EPI, SDG, HDI, and WGI, to assess their sustainability performance from a multidimensional perspective. This will provide a more objective, comparable, and analytical framework for presenting the relative sustainability performance of countries.

One of the unique contributions of this study is its joint assessment of sustainability performance not only through level indicators (SDG Index, EPI, HDI, WGI, Gini, CO_2, etc.) but also through the SUI (ESGUI) index, which reflects the extent of uncertainty related to sustainability policies. While the number of SUI/ESGUI-based studies in the literature is quite limited, this study integrates this index into a MCDM approach to analyze countries' sustainability performance holistically along the "level + uncertainty" axes. Thus, while traditional indicators reflect only environmental, social, and institutional outcomes, the SUI (ESGUI) index integrates policy uncertainty, which shapes these outcomes, into the model. In this respect, the study offers a unique contribution to the literature as one of the rare empirical applications that considers sustainability performance and sustainability uncertainty within the same framework.

In this regard, the subsequent sections of the study are structured as follows: The following section summarizes the relevant literature focusing on indicators such as sustainability uncertainty, environmental performance, income inequality, and governance, and outlines the theoretical framework of the study. In the methodology section, the scope of the SUI, CO_2, Gini, API, EPI, SDG, HDI, and WGI data sets used in the analysis is defined, the rationale for the selection of criteria is explained, and the application steps of the integrated CRITIC-EDAS approach are detailed. The findings section presents the relative sustainability rankings of countries, along with sensitivity analyses supported by Monte Carlo simulations that test the model's consistency. The conclusion section discusses the findings in comparison with the existing literature, develops concrete recommendations for policymakers, and provides directions for future studies.

2. Literature review

Multidimensional indicators, including sustainability uncertainty, environmental pressure, income distribution equity, renewable energy transition, environmental performance, sustainable development achievement, human development level, and rule of law, were used to analyze countries' sustainability performance. To this end, Table 1 systematically summarizes the definitions of each criterion used in the study: SUI/ESGUI, per capita CO_2 emissions, Gini index, API, EPI, SDG, HDI, and WGI, along with selected empirical studies based on these indicators. This provides the theoretical basis for the multidimensional sustainability framework used in the analysis.

Table 1. Criterion-Based Literature Table

Criterion	Definition	Selected Study
ESGSUI – ESG-based Sustainability Uncertainty Index	The ESGUI is a text-mining-based composite index developed to measure countries' sustainability-related uncertainty levels. First proposed by Ongan et al. (2025), the index calculates three sub-indices based on the frequency of keywords related to environmental (E), social (S), and governance (G) selected from the monthly country reports of the Economist Intelligence Unit (EIU). An uncertainty sub-index derived from phrases such as "uncertain/uncertainty" in the same reports is added. These four components are normalized and scaled to a range of 0-100, producing monthly ESGUI series for 25 countries. Global ESGUI indices are also generated using equally weighted and GDP-weighted averages of the country series (policyuncertainty.com).	Ongan et al. (2025) utilize a new indicator called N-ESG, which is derived by subtracting ESGUI from ESG scores; thus, they argue that the ESG performance of firms/countries should be adjusted to account for sustainability uncertainty. ESGUI is used here as a quantitative measure of sustainability uncertainty. Nyakurukwa et al. (2025) examine the global and regional spread of ESG policy uncertainty, utilizing ESGUI as a new composite sustainability uncertainty indicator to analyze how the developed ESG policy uncertainty indicators are disseminated across developed and emerging markets. Zeren et al. (2025), taking ESGUI as the dependent variable for G7 countries, analyze the macroeconomic, financial, and institutional determinants of sustainability uncertainty using asymmetric Fourier methods. Anbea et al. (2025) use ESGUI as an indicator of "ESG sustainability uncertainty" while examining the relationship between energy preferences and ESG sustainability in developed economies. They test the effects of energy preferences and education/integration policies on sustainability uncertainty. Gaies (2025) analyze the interaction between financial instability and climate risks using the U.S. ESG-based Sustainability Uncertainty Index (ESGUI) series for the United States, demonstrating that ESGUI serves as a macro uncertainty indicator that can reveal the sensitivity of financial markets to sustainability shocks.
CO_2 – CO_2 Emission per capita	Per capita CO_2 emissions are measured as the ratio of carbon dioxide emissions from fossil fuel consumption and cement production to the country's population in tonnes per capita. This indicator, reported in the World Bank's World Development Indicators (WDI) database, is designated by the code EN.ATM.CO2E.PC is considered a key measure of environmental pressure (World Bank 2024a).	Per capita CO_2 emissions are used as one of the main variables representing environmental pressure in global sustainability and competitiveness studies; for example, Agan (2024) uses the per capita CO_2 series from WDI in his analysis of global sustainable competitiveness and environmental sustainability. In addition, in multi-criteria or panel-based studies, such as those by Guijarro and Poyatos (2019) and Agan (2024), CO_2 is considered an integral component of composite indices that evaluate the environmental performance of countries. Akpolat (2024) examines the relationship between CO_2 per capita emissions, fossil, API, and sustainability using panel data. Rosa and Jadotte (2023) analyzes the determinants

		of per capita CO_2 emission inequality among developing countries. Liu et al. (2023) examine the dynamics of infrastructure development, HDI, and per capita CO_2 emissions. Shabani (2024) examines the impact of API and human capital on CO_2 emissions using panel data, showing that renewable energy reduces emissions while human capital strengthens this relationship. Nguyen et al. (2025) analyze the impact of digital infrastructure and renewable energy on CO_2 emission intensity for 217 countries, finding that the growth of digital infrastructure and renewable energy reduces emission intensity. Pal et al. (2025) demonstrate the short- and long-term effects of economic indicators, API, and HDI on carbon emissions in selected Asian countries using panel ARDL.
GINI – Poverty and Income Inequality Index	The Gini index is an indicator measuring the degree to which income distribution deviates from perfect equality, taking values between 0 (perfect equality) and 100 (perfect inequality). It is reported by the World Bank as "Gini index (World Bank estimate)" with the code SI.POV.GINI; the index is calculated using the Lorenz curve of income or consumption distribution based on household survey data (World Bank 2024b).	The Gini index is widely used as a basic measure of income distribution equity in studies of sustainable development and inequality. For example, Makhlouf (2023) examines the income inequality dynamics of 34 countries for the period 1960-2020 using the Gini index and discusses the relationship between inequality trends and the Sustainable Development Goals. World Bank data are also used as a standard data source in empirical analyses of the inequality dimension within the framework of SDGs (Makhlouf 2023; World Bank 2024b). Haddad et al. (2024). Discusses the interpretation of the Gini coefficient in the context of the World Bank "new inequality indicator". Bi (2020) evaluates the sustainable development performance of countries by integrating the Gini coefficient into the human sustainable development index. Dvulit et al. (2025) examine the relationship between SDG 3 (Health and Well-being) and SDG 10 (Reduced Inequalities) for the EU and Ukraine in the period 2009-2021, using classification, clustering, and regression analyses on the Gini coefficient. The results show that a decrease in income inequality improves health indicators.
API – Renewable Energy Consumption	API is a percentage indicator that shows the share of renewable energy sources (such as hydro, wind, solar, and biomass) in total final energy consumption. It is presented as "API (% of total final energy consumption)" in the World Bank WDI database with the code EG.FEC.RNEW.ZS (World Bank 2024c).	This indicator is widely used in the energy transition, green growth, and environmental sustainability literature to measure the level of countries' transition to low-carbon energy systems. Maji and Sulaiman (2019) use this indicator when analyzing the relationship between API and economic growth in West African countries. Xu and Gallagher (2022) use API rates in their study examining the role of development finance institutions in green energy transition. Liao (2023) use the API rate as the main indicator for the sustainable impacts of green energy projects. Chuong (2025) analyze the relationship between globalization, renewable energy, and sustainable development for 104 countries, with API serving as the primary determinant. Shabani (2024) examines the relationship between renewable API energy consumption and CO_2, and by including human capital in the model, they emphasize the emission-reducing effect of increasing the renewable energy share. Nguyen et al. (2025) test the role of API in reducing CO_2 emission intensity separately for countries in different income groups. Pal et al. (2025) confirm that API significantly reduces carbon emissions in the long run, as indicated by panel ARDL and FMOLS/DOLS results.
EPI – Environmental Performance Index	The EPI is a composite index that summarizes countries' environmental performance on a scale of 0-100, combining more than 50 indicators across areas such as climate change, environmental health, and ecosystem vitality. Published biannually by	The EPI is frequently used in comparing countries' environmental performance and in multi-criteria assessments focused on environmental sustainability. Guijarro and Poyatos (2019) utilize EPI components when evaluating countries' environmental performance using a MCDM approach; Ekinci and Oturakçı (2025)

	the Yale University Center for Environmental Law and Policy and Columbia University, the EPI is a comprehensive measure that shows how well countries are approaching their environmental policy goals (Block et al. 2024; Yale Center for Environmental Law and Policy, 2024).	analyze Turkey's environmental performance using the EPI index values. Recently, the EPI has become a reference index whose sensitivity to different normalization and weighting scenarios has been debated (Ekinci and Oturakçı 2025; Guijarro and Poyatos 2019). Pinar (2022) analyze the EPI's sensitivity to different normalization and weighting methods. Wendling et al. (2022) propose a framework for explaining countries' environmental performance based on the EPI. They analyze the effects of determinants such as governance, income level, and structural factors on the EPI and discuss how the EPI can be used for policy design.
SDG – Sustainable Development Score	The SDG Index is a composite index that combines numerous social, economic and environmental indicators related to the 17 Sustainable Development Goals to produce a SDG and ranking for countries on a scale of 0-100. It is prepared by the Sustainable Development Solutions Network (SDSN). Sustainable Development Report series is updated every year (Sachs et al. 2023).	The SDG Index has become one of the main reference indicators for comparatively analyzing country progress towards the SDGs. Sachs et al. (2023) relate the index to global policy recommendations within the framework of the "SDG Stimulus", while many empirical studies use SDG scores in conjunction with governance indicators, income inequality, or environmental indicators to examine the determinants of countries' sustainable development performance (Sachs et al. 2023; Blancas et al. 2025). The WGI analyzes the relationship between governance indicators and SDG performance and the impact of governance quality on SDG achievement (Bisogno et al. 2025). In various studies of the SDSN, the SDG Index is used as a core indicator for comparatively evaluating country sustainability performance. Dvulit et al. (2025) examine the interaction between SDG 3 and SDG 10 by combining SDG indicators with the Gini coefficient; It clusters countries according to both their level of SDG achievement and their level of inequality.
HDI – Human Development Index	The HDI is a composite index that summarizes average achievement in three key dimensions of human development: a long and healthy life, education, and a decent standard of living. It is calculated on a scale of 0-1 based on the geometric mean of life expectancy, education (expected and mean years of schooling), and GDP per capita (GNI, PPP) (UNDP, 2024).	The HDI is one of the most widely used composite indicators in discussions of human development, inequalities, poverty, and sustainable development. The UNDP Human Development Report 2023/24 interprets the HDI as a key indicator of global inequalities and development bottlenecks, referred to as "gridlocks" (UNDP 2024a). Many empirical studies examine the relationships between human development and environmental and economic sustainability by using the HDI together with indicators such as CO_2 emissions, renewable energy use or institutional quality. Castells-Quintana and López-Bazo (2019). Analyze the relationship between income inequality and human development using HDI data. Liu et al. (2023) examine the interaction between infrastructure development, carbon emissions and HDI with panel data. Kozal (2024). Analyze environmental sustainability indicators using CO_2, renewable energy and HDI together. Pal et al. (2025) include the HDI among the determinants of climate change, finding that economic growth and industrialization, as well as human development, have a complex relationship with carbon emissions, and that renewable energy and human development can contribute to a more sustainable emission pathway in the long run. Nguyen et al. (2025) also use socioeconomic variables such as the HDI and structural indicators as

		control variables in their model explaining CO_2 emission intensity.
WGI – Rule of Law Index	The "Rule of Law (RL.EST)" indicator, part of the World Bank's Worldwide Governance Indicators (WGI), is a composite governance index that measures public perceptions of trust in and compliance with rules across dimensions such as contract enforcement, property rights, police and judicial quality, and the risk of crime and violence. The indicator ranges from approximately −2.5 to +2.5 (Kaufmann et al. 2010; World Bank 2024d).	The rule of law indicator within the WGI is widely used in the sustainable development and institutional economics literature to measure the quality of governance and the strength of democratic institutions. Kaufmann et al. (2010) provide a detailed explanation of the WGI methodology, and many subsequent studies have linked rule of law scores to SDG performance, environmental policy effectiveness, or economic growth (Kaufmann et al. 2010; World Bank 2024d). Bisogno et al. (2025) examine the relationship between WGI indicators and SDG performance, testing the impact of the rule of law and other governance dimensions on sustainable development. Mahmutović and Alhamoudi (2024) examine the relationship between the rule of law and sustainable development within a conceptual and normative framework, arguing that rule of law institutions are fundamental to the achievement of the 2030 Agenda and the SDGs.

When the studies summarized in the table are considered as a whole, it is evident that the literature constructs the sustainability profiles of countries mostly based on fragmented indicators. Studies focusing on CO_2 emissions, API, and environmental performance (Akpolat 2024; Shabani 2024; Pal et al. 2025; Nguyen et al. 2025; Wendling et al. 2022; Guijarro and Poyatos 2019; Ekinci and Oturakçı 2025) focus primarily on environmental pressure and energy transition, while the inequality and human development literature (Makhlouf 2023; Bi 2020; Castells-Quintana and López-Bazo 2019) deepens the social dimension through the Gini and HDI, while often leaving environmental and institutional indicators in the background.

Although SDG and governance-based analyses (Sachs et al. 2023; UN DESA 2023; Bisogno et al. 2025; Dvulit et al. 2025) link sustainable development achievement and WGI-based institutional quality, these studies generally use ready-made composite indices (SDG Index, WGI) directly and focus on two- to three-dimensional relationships rather than establishing a detailed set of criteria including CO_2, EPI, inequality and human development. A newer vein, the ESG-based sustainability uncertainty literature (Ongan et al. 2025; Nyakurukwa et al. 2025; Gaies 2025; Zeren et al. 2025), treats ESGUI either as a dependent variable (G7, financial instability, etc.) or as a single uncertainty indicator alongside certain financial/energy indicators; Studies that embed ESGUI into a multi-criteria country sustainability ranking, along with CO_2, Gini, API, EPI, SDG, HDI and WGI, remain extremely limited.

This study offers a complementary and distinctive aspect to this literature on two levels. First, it combines sustainability uncertainty (ESGUI/SUI), per capita CO_2 emissions, income inequality (Gini), API, EPI, SDG, HDI, and WGI indicators into a single, consistent set of criteria to assess countries' sustainability performance within a multidimensional framework encompassing environmental, social, institutional, and uncertainty dimensions. Second, unlike previous studies, where composite indices such as the SDG Index or EPI are mostly based on normative or expert-based weighting approaches (Pinar 2022; Sachs et al. 2023), this research determines the criteria weights using CRITIC, an objective method based on the information content of the data.

It then ranks countries based on positive and negative deviations from the mean solution using the EDAS method. Thus, indicators generally used in regression or wavelet/measurement models in the literature, especially ESGUI, are positioned here for the first time as components of an objectively weighted multi-criteria sustainability index; countries are evaluated within a transparent and comparable MCDM framework, taking into account both the level of sustainability and sustainability uncertainty, and in this respect, the study offers an original contribution that distinguishes it from the existing literature.

3. Methodology

To assess the sustainability performance of countries, an analysis was conducted using Multi-Criteria Decision Making Techniques (MCDM) using data from 2023. The year 2023 was chosen because the most up-to-date data regarding these countries is concentrated in that year. In this study, the CRITIC and EDAS techniques from MCDM were used in two stages. In the first stage, the criteria were weighted using the CRITIC method. In the second stage, the alternatives were evaluated using the EDAS method. Furthermore, the criteria used in the study, their sources, the direction of preference in the normalization process, and the codes are shown in Table 2. Table 3 shows the countries and their codes used in the study.

Table 2. Criteria used in the study

Criteria	Explanation	Preference	Year	Source
SUI	ESG-Based Sustainability Uncertainty Index	Min	2023	ESGUI†
CO_2	CO_2 Emissions per Capita	Min	2023	Dünya Bankası
GINI	Poverty and Equality Index	Min	2021-2023‡	Dünya Bankası
API	Renewable Energy Consumption	Max	2021§	Dünya Bankası
EPI	Environmental Performance Index	Max	2024**	Yale University
SDG	Sustainable Development Score	Max	2023	SDSN††
HDI	Human Development Index	Max	2023	UNDP‡‡
WGI	Rule of Law Index	Max	2023	Dünya Bankası

Table 3. List of countries in the study

Countries	Code	Countries	Code	Countries	Code	Countries	Code	Countries	Code
Australia	A1	China	A6	India	A11	Netherlands	A16	Spain	A21
Belgium	A2	Colombia	A7	Ireland	A12	Pakistan	A17	Sweden	A22
Brazil	A3	France	A8	Italy	A13	Russia	A18	UK	A23
Canada	A4	Germany	A9	Japan	A14	Singapore	A19	US	A24
Chile	A5	Greece	A10	Mexico	A15	S Korea	A20	Vietnam	A25

3.1. Selection of weighting method

In this study, to determine the most appropriate weighting method that will accurately reflect the importance of critical variables such as sustainability uncertainty (SUI) and environmental pressure (CO_2) within the dataset, which form the main axis of the study, and ensure the consistency of the analysis results; the weight coefficients produced by the Entropy, MEREC, LOPCOW, and CRITIC methods, which are widely used in the literature, were comparatively evaluated. The comparison of the weighting methods related to these methods is presented in Table 4.

The Entropy method focused on the irregularity in the distribution of data but assigned a negligible weight (0.005) to the SUI (Uncertainty) criterion, which is the most critical variable in the study. This situation demonstrates that the Entropy method is insufficient in reflecting the emphasis on uncertainty in this dataset.

The MEREC method has assigned a disproportionately high weight (0.285) to the WGI criterion. The dominance of a social indicator in this analysis has overshadowed environmental and uncertainty factors.

† https://www.policyuncertainty.com/sustainability_index.html
‡ It was determined based on data shared by countries in recent years (2021-2023).
§ The latest data was shared in 2021.
** The year 2024 was chosen because it is published biennially.
†† Sustainable Development Solutions Network
‡‡ United Nations Development Program

The LOPCOW method, on the other hand, has shifted the weight significantly towards general development indicators such as HDI (0.172) and SDG (0.169). These risks transforming the analysis into a "Classic Development Ranking".

The CRITIC method is the only method that assigns the highest weights to the SUI (Uncertainty) criterion (0.166) and CO_2 Emissions (0.168), which are the main themes of the study. CRITIC balances the weight of repetitive information by considering the correlation between data (such as the SDG-HDI-WGI relationship) and highlights the SUI criterion, which carries more unique information.

To preserve the decisiveness of the "Uncertainty Index" concept emphasized in the study's title and to ensure environmental/social balance most rationally, using the CRITIC weighting method would be the most appropriate choice.

Table 4. Comparison of weighting methods

Criteria	Code	CRITIC	MEREC	LOPCOW	Entropi
ESG-Based Sustainability Uncertainty Index	SUI	0.166 (2)	0.089 (7)	0.094 (7)	0.005 (8)
CO_2 Emissions per Capita	CO_2	0.168 (1)	0.106 (3)	0.113 (6)	0.145 (4)
Poverty and Equality Index	GINI	0.119 (5)	0.091 (6)	0.144 (3)	0.126 (6)
Renewable Energy Consumption	API	0.132 (3)	0.153 (2)	0.073 (8)	0.176 (1)
Environmental Performance Index	EPI	0.110 (6)	0.099 (4)	0.119 (4)	0.132 (5)
Sustainable Development Score	SDG	0.078 (8)	0.086 (8)	0.169 (2)	0.127 (7)
Human Development Index	HDI	0.100 (7)	0.091 (5)	0.172 (1)	0.127 (6)
Rule of Law Index	WGI	0.128 (4)	0.285 (1)	0.116 (5)	0.163 (2)
Total		**1.000**	**1.000**	**1.000**	**1.000**

3.2. Selection of ranking method

In this study, the EDAS (Evaluation Based on Distance from Average Solution) method was employed for ranking countries based on their sustainability uncertainty and ESG performance (Keshavarz Ghorabaee et al. 2015). Methods such as TOPSIS and VIKOR, frequently used in the MCDM literature, evaluate alternatives based on their distance from the "Ideal" and "Anti-Ideal" endpoints. However, the SUI and CO_2 Emission data, which are the focus of this study, have the potential to contain high variation and outliers between countries. Methods based on the ideal point can be overly influenced by these outliers, causing ranking deviations. In contrast, the EDAS method performs the evaluation based on the "Average Solution" rather than outliers. This algorithm, which calculates the positive (PDA) and negative (NDA) deviations of alternatives from the average, mitigates excessive fluctuations in the dataset and provides a more robust and consistent ranking in an uncertain environment. Furthermore, preliminary analyses have determined that the EDAS method provides the highest correlation with other ranking techniques (see Table 5), statistically validating the method's validity. Table 6 presents a comparative evaluation of the applied MCDM techniques, highlighting the ranking results for each country.

Table 5. Correlation results

	ARAS	WASPAS	AROMAN	MABAC	Multimoora	EDAS	Cradis	Average
ARAS	1	0,552	0,697	0,684	0,681	0,853	0,328	0,816
WASPAS	0,552	1	0,493	0,504	0,484	0,602	0,320	0,676
AROMAN	0,697	0,493	1	0,97	0,714	0,857	0,508	0,899
MABAC	0,684	0,504	0,97	1	0,776	0,868	0,604	0,928
Multimoora	0,681	0,484	0,714	0,776	1	0,771	0,704	0,873
EDAS	0,853	0,602	0,857	0,868	0,771	1	0,504	0,933
Cradis	0,328	0,320	0,508	0,604	0,704	0,504	1	0,663

Despite the methodological differences between TOPSIS, which is based on the ideal solution, and VIKOR, which is based on the compromise solution, the fact that the EDAS method achieves high compatibility with both approaches demonstrates that the method's "Average Solution" approach provides the best "Consensus" for this data set. The EDAS method not only produced results consistent with other methods but also provided the most balanced ranking by preventing extreme values derived from SUI (Uncertainty) data from manipulating the ranking.

Table 6. Comparison between methods

Country	Code	ARAS	WASPAS	AROMAN	MABAC	Multimoora	EDAS	CRADIS	Average
Australia	A1	10	6	14	13	12	12	18	11
Belgium	A2	12	5	7	6	10	8	10	7
Brazil	A3	14	21	12	14	22	14	23	18
Canada	A4	8	17	16	15	3	11	19	13
Chile	A5	18	10	19	20	8	15	2	14
China	A6	23	22	23	22	17	23	12	21
Colombia	A7	21	14	22	23	23	21	22	23
France	A8	7	24	6	5	4	6	1	6
Germany	A9	3	3	3	3	2	4	11	3
Greece	A10	20	12	11	10	11	19	5	12
India	A11	9	9	5	12	15	10	21	10
Ireland	A12	6	4	8	7	4	5	9	4
Italy	A13	19	20	9	9	12	18	6	15
Japan	A14	11	7	10	8	14	7	13	8
Mexico	A15	24	15	21	21	24	24	24	24
Netherlands	A16	2	18	4	4	6	3	8	5
Pakistan	A17	5	13	24	25	21	22	20	20
Russia	A18	25	23	25	24	25	25	15	25
Singapore	A19	13	11	18	18	18	9	14	16
S Korea	A20	17	16	17	16	18	16	16	17
Spain	A21	15	8	13	11	6	13	7	9
Sweden	A22	1	1	1	1	1	1	4	1
UK	A23	4	2	2	2	9	2	3	2
US	A24	16	19	20	19	16	17	17	19
Vietnam	A25	22	25	15	17	20	20	25	22

3.3. CRITIC and EDAS multi-criteria decision-making methods

In the MCDM literature, the CRITIC (Criteria Importance Through Intercriteria Correlation) method is an objective weighting approach that determines criterion weights entirely based on data. The method first calculates the standard deviation value through the normalized decision matrix to measure the discriminative power of each criterion, then evaluates the information overlap between criteria using Pearson correlation coefficients. Thus, criteria that are both highly variable (strongly distinguishing decision alternatives) and highly unrelated to other criteria are considered to have higher information content and, accordingly, receive higher weights. Due to these characteristics, the CRITIC method reduces decision-maker subjectivity by allowing the data structure to determine the importance of criteria and is widely used in the literature, particularly for multidimensional problems such as financial performance, sustainability, and supplier selection (Diakoulaki et al. 1995; Zardari et al. 2015; Keshavarz Ghorabaee et al. 2015). Table 7 details the solution steps of the CRITIC method.

Table 7. CRITIC method solution steps

No	Equation	Explanation
(1)	$r_{ij} = \frac{x_{ij} - x_j^{min}}{x_j^{max} - x_j^{min}}$ *Benefit* $r_{ij} = \frac{x_j^{max} - x_{ij}}{x_j^{max} - x_j^{min}}$ *Cost*	The decision matrix is normalized according to the benefit/cost characteristics.
(2)	$r_j = \frac{1}{m}\sum_{i=1}^{m} r_{ij}$ $Q_j = \sqrt{\frac{1}{m}\sum_{i=1}^{m}(r_{ij} - r_j)^2}$	Using the normalized decision matrix, the mean and standard deviation of each criterion are calculated. The standard deviation indicates the criterion's discrimination.
(3)	$p_{jk} = \frac{\sum_{i=1}^{m}(r_{ij} - r_j).(r_{ik} - r_k)}{\sqrt{\sum_{i=1}^{m}(r_{ij} - r_j)^2}.\sqrt{\sum_{i=1}^{m}(r_{ik} - r_k)^2}}$	The linear relationship between the criteria is measured by the Pearson correlation coefficient. This determines the extent to which a criterion conveys similar information to other criteria.
(4)	$C_j = \sigma_j.\sum_{k=1}^{n}(1 - p_{jk})$	The total amount of information carried by each criterion (C_j) is calculated by combining the criterion's standard deviation with its uncorrelatedness ($1 - p_{jk}$).
(5)	$w_j = \frac{C_j}{\sum_{j=1}^{n} C_j}$	The CRITIC criterion weights are obtained by normalizing the information content of each criterion. The total weight is equal to 1.

Table 8. EDAS method solution steps

No	Equation	Explanation
(6)	$AV_j = \frac{\sum_{i=1}^{n} X_{ij}}{m}$	Calculating the Average Solution
(7)	$PDA_{ij} = \frac{max(0,(X_{ij} - AV_j))}{AV_j}$; $PDA_{ij} = \frac{max(0,(AV_j - X_{ij}))}{AV_j}$	Calculating the Positive Distance Matrix from the Average Solution
(8)	$NDA_{ij} = \frac{max(0,(AV_j - X_{ij}))}{AV_j}$; $NDA_{ij} = \frac{max(0,(X_{ij} - AV_j))}{AV_j}$	Calculating the Negative Distance Matrix from the Average Solution
(9)	$SP_i = \sum_{j=1}^{m} w_j * PDA_{ij}$	Calculating the Sum of Positive Distances
(10)	$SN_i = \sum_{j=1}^{m} w_j * NDA_{ij}$	Calculating the Sum of Negative Distances
(11)	$NSP_i = \frac{SP_i}{max(SP_i)}$	Normalized Sum of Positive Distances
(12)	$NSN_i = 1 - \frac{SN_i}{max(SN_i)}$	Normalized Sum of Negative Distances
(13)	$AS_i = \frac{1}{2}(NSP_i + NSN_i)$	Calculating the Final Value

The EDAS (Distance-Based Evaluation from the Average Solution) method, proposed by Keshavarz Ghorabaee et al. (2016), is a relatively new and robust methodology for solving MCDM problems. The basic philosophy of the method is that the attractiveness of an alternative is determined by its performance across all criteria and its distance from the average solution. EDAS calculates the Positive Distance and Negative Distance matrices of the other options relative to the average solution. For benefit criteria, a value above the average creates a positive distance, while for cost criteria, a value below the average creates a positive distance. These two distances are summed and normalized using the criteria weights. Finally, the final evaluation score obtained by combining the normalized positive and negative distances is used to rank the alternatives. This method is a simple and computationally efficient tool that has proven particularly effective in highly competitive evaluation scenarios where deviations from the criteria's average are significant (Keshavarz Ghorabaee et al. 2016a). Table 8 details the solution steps of the EDAS method.

EDAS is recommended as an alternative approach to classical methods such as TOPSIS and VIKOR in both theoretical and applied studies because it does not require the determination of ideal and anti-ideal solutions, captures relative performance compared to the average, and can be adapted to different extensions (fuzzy, intuitionistic fuzzy, pictorial fuzzy, etc.) (Keshavarz Ghorabaee et al. 2015; Yalçın and Uncu 2019; Torkayesh et al. 2023).

4. Results

All CRITIC and EDAS stages for each country are tabulated. The full analysis processes for other MCDM methods (MABAC, ARAS, WASPAS, AROMAN, etc.) are not provided. Relevant tables are available upon request. In the first stage, the criteria are weighted using the CRITIC method. The initial decision matrix, created before the weighting process, is presented in Table 9.

Table 9. Decision matrix

Code/Criteria	SUI	CO_2	Gini	API	EPI	SDG	HDI	WGI
A1	28,59	14,5	33,8	12,3	63,1	77,6	0,958	2,713
A2	36,79	7,2	26,8	11,7	66,8	80,5	0,951	2,485
A3	21,39	2,3	51,6	46,5	53	73,7	0,786	0,881
A4	42,69	13,9	31,1	23,8	61,1	79,3	0,939	2,663
A5	46,57	3,9	43	24,2	49,6	78,2	0,878	1,815
A6	31,85	8,6	36	15,2	35,4	74,2	0,797	1,15
A7	37,79	1,7	53,9	29,7	49,7	70,3	0,788	0,732
A8	36,19	4,1	31,8	16,2	67	83,2	0,92	2,371
A9	33,89	7	32,4	17,6	74,5	83,6	0,959	2,741
A10	33,76	5,1	33,4	21,5	67,3	79,2	0,908	1,403
A11	21,76	2,1	25,5	34,9	27,6	66,7	0,685	1,378
A12	43,98	6,5	29	12,7	65,8	78,7	0,949	2,824
A13	31,36	5,2	34,3	17,5	60,3	80,2	0,915	1,58
A14	38,06	7,9	32,3	8,8	61,4	80,2	0,925	2,726
A15	22,11	3,5	43,5	13	44,2	70,8	0,789	0,384
A16	36,59	6,5	25,7	12,2	66,9	80	0,955	2,833
A17	40,49	0,8	29,6	41,6	25,5	56,9	0,544	0,33
A18	17,00	11,9	33	3,5	46,7	74,1	0,832	0,002
A19	36,41	8,8	43,5	1,1	53	70	0,946	2,943
A20	32,64	11,4	32,9	3,6	50,6	78,1	0,937	2,439
A21	43,09	4,5	33,4	19	64	80,8	0,918	2,013
A22	38,98	3,5	29,3	57,9	70,3	86,1	0,959	2,794
A23	28,67	4,5	32,4	12,2	72,6	81,8	0,946	2,588
A24	32,13	14,3	41,8	10,9	57,2	75,1	0,938	2,518
A25	21,61	3,5	36,1	24,2	24,6	73,1	0,766	1,105
Max	46,57	14,50	53,90	57,90	74,50	86,10	0,96	1,75
Min	17,00	0,80	25,50	1,10	24,60	56,90	0,54	0,00

Table 9 presents the raw dataset on countries' sustainability performance, showing each country's absolute position on indicators such as sustainability uncertainty (SUI), CO_2 emissions per capita, income inequality (Gini), renewable energy use (API), environmental performance (EPI), SDG, human development level (HDI), and rule of law (WGI). The table presents a multidimensional sustainability profile that combines both cost (SUI, CO_2, Gini) and benefit (API, EPI, SDG, HDI, WGI) indicators within a single framework, highlighting significant differences across countries based on environmental, social, and governance factors.

In Table 10, the raw indicators in the decision matrix have been normalized to account for cost-benefit considerations, making variables with different scales and units comparable. Moving the criteria to a range of 0 to 1 after normalization provides a clearer picture of relative positions across countries; while there is particularly high variation in the WGI, EPI, SDG, and Gini indicators, the distribution is relatively more balanced for some criteria. This step provides the necessary statistical basis for calculating criteria weights based on their information content using the CRITIC method.

Table 10. CRITIC normalized decision matrix

Code/Criteria	SUI	CO_2	Gini	API	EPI	SDG	HDI	WGI
A1	0,61	0,00	0,71	0,20	0,77	0,71	1,00	1,55
A2	0,33	0,53	0,95	0,19	0,85	0,81	0,98	1,42
A3	0,85	0,89	0,08	0,80	0,57	0,58	0,58	0,50
A4	0,13	0,04	0,80	0,40	0,73	0,77	0,95	1,52
A5	0,00	0,77	0,38	0,41	0,50	0,73	0,80	1,04
A6	0,50	0,43	0,63	0,25	0,22	0,59	0,61	0,66
A7	0,30	0,93	0,00	0,50	0,50	0,46	0,59	0,42
A8	0,35	0,76	0,78	0,27	0,85	0,90	0,91	1,35
A9	0,43	0,55	0,76	0,29	1,00	0,91	1,00	1,56
A10	0,43	0,69	0,72	0,36	0,86	0,76	0,88	0,80
A11	0,84	0,91	1,00	0,60	0,06	0,34	0,34	0,79
A12	0,09	0,58	0,88	0,20	0,83	0,75	0,98	1,61
A13	0,51	0,68	0,69	0,29	0,72	0,80	0,89	0,90
A14	0,29	0,48	0,76	0,14	0,74	0,80	0,92	1,56
A15	0,83	0,80	0,37	0,21	0,39	0,48	0,59	0,22
A16	0,34	0,58	0,99	0,20	0,85	0,79	0,99	1,62
A17	0,21	1,00	0,86	0,71	0,02	0,00	0,00	0,19
A18	1,00	0,19	0,74	0,04	0,44	0,59	0,69	0,00
A19	0,34	0,42	0,37	0,00	0,57	0,45	0,97	1,68
A20	0,47	0,23	0,74	0,04	0,52	0,73	0,95	1,39
A21	0,12	0,73	0,72	0,32	0,79	0,82	0,90	1,15
A22	0,26	0,80	0,87	1,00	0,92	1,00	1,00	1,59
A23	0,61	0,73	0,76	0,20	0,96	0,85	0,97	1,48
A24	0,49	0,01	0,43	0,17	0,65	0,62	0,95	1,44
A25	0,84	0,80	0,63	0,41	0,00	0,55	0,53	0,63

Table 11. Bileteral correlation matrix

	SUI	CO_2	Gini	API	EPI	SDG	HDI	WGI
SUI	1,00	-0,02	-0,15	-0,06	-0,38	-0,26	-0,31	-0,50
CO_2	-0,02	1,00	-0,14	0,59	-0,25	-0,25	-0,53	-0,40
Gini	-0,15	-0,14	1,00	-0,09	0,18	0,26	0,16	0,37
API	-0,06	0,59	-0,09	1,00	-0,20	-0,17	-0,45	-0,26
EPI	-0,38	-0,25	0,18	-0,20	1,00	0,83	0,86	0,69
SDG	-0,26	-0,25	0,26	-0,17	0,83	1,00	0,87	0,64
HDI	-0,31	-0,53	0,16	-0,45	0,86	0,87	1,00	0,80
WGI	-0,50	-0,40	0,37	-0,26	0,69	0,64	0,80	1,00

Table 11 illustrates the linear relationships between the criteria, which form the basis of the CRITIC method. An examination of the table reveals high positive correlations (above 0.80), particularly among EPI, SDG, and HDI; this indicates that these indicators convey similar information and create informational redundancy. Conversely, the fact that the SUI criterion—the focal point of this study—exhibits negative correlations with most other criteria (especially WGI and EPI) demonstrates that this criterion introduces distinct and discriminative information to the dataset.

Table 12. Critic weighting results

	SUI	CO_2	Gini	API	EPI	SDG	HDI	WGI
Q_j	0,26697	0,29381	0,25845	0,24054	0,29138	0,21456	0,24987	0,52857
C_j	2,31751	2,34822	1,65487	1,83805	1,53281	1,08775	1,39901	2,99383
w_j	0,15275	0,15477	0,10907	0,12115	0,10103	0,07169	0,09221	0,19733
Rank	2	1	5	3	6	8	7	4

Table 12 summarizes the stage where criterion importance levels (weights) are objectively determined by considering the standard deviation and correlation structure of the data. The results indicate that criteria such as WGI (0.197) and CO_2 (0.154) received the highest weights due to their high variation and discriminative power within the dataset.

The substantial weight assigned to the SUI criterion (0.152) further indicates that the uncertainty factor plays a critical role in differentiating countries' sustainability performances, confirming that the CRITIC method successfully captures this "conflicting" information.

Table 13. EDAS positive distance values from the mean

Code/Criteria	SUI	CO_2	Gini	API	EPI	SDG	HDI	WGI
A1	0,143	0,000	0,035	0,000	0,145	0,014	0,094	0,431
A2	0,000	0,000	0,235	0,000	0,212	0,052	0,086	0,310
A3	0,359	0,648	0,000	1,364	0,000	0,000	0,000	0,000
A4	0,000	0,000	0,113	0,210	0,108	0,037	0,073	0,404
A5	0,000	0,403	0,000	0,230	0,000	0,022	0,003	0,000
A6	0,046	0,000	0,000	0,000	0,000	0,000	0,000	0,000
A7	0,000	0,740	0,000	0,510	0,000	0,000	0,000	0,000
A8	0,000	0,372	0,093	0,000	0,215	0,088	0,051	0,250
A9	0,000	0,000	0,075	0,000	0,351	0,093	0,095	0,445
A10	0,000	0,219	0,047	0,093	0,221	0,035	0,037	0,000
A11	0,348	0,678	0,272	0,774	0,000	0,000	0,000	0,000
A12	0,000	0,004	0,172	0,000	0,194	0,029	0,084	0,489
A13	0,060	0,203	0,021	0,000	0,094	0,048	0,045	0,000
A14	0,000	0,000	0,078	0,000	0,114	0,048	0,057	0,437
A15	0,337	0,464	0,000	0,000	0,000	0,000	0,000	0,000
A16	0,000	0,004	0,267	0,000	0,214	0,046	0,091	0,494
A17	0,000	0,877	0,155	1,115	0,000	0,000	0,000	0,000
A18	0,491	0,000	0,058	0,000	0,000	0,000	0,000	0,000
A19	0,000	0,000	0,000	0,000	0,000	0,000	0,081	0,552
A20	0,022	0,000	0,061	0,000	0,000	0,021	0,070	0,286
A21	0,000	0,311	0,047	0,000	0,161	0,056	0,049	0,061
A22	0,000	0,464	0,164	1,943	0,275	0,126	0,095	0,473
A23	0,141	0,311	0,075	0,000	0,317	0,069	0,081	0,365
A24	0,037	0,000	0,000	0,000	0,038	0,000	0,071	0,328
A25	0,352	0,464	0,000	0,230	0,000	0,000	0,000	0,000

Representing the initial computational step of the EDAS method, Table 13 displays the extent to which countries exceed the "average performance" (or fall below it for cost criteria) on a criterion-by-criterion basis. The high values observed for countries such as Sweden (A22) and Brazil (A3) in specific columns suggest that these nations derive a competitive advantage by deviating significantly positively from the mean in those respective areas (e.g., Brazil's score in the renewable energy API). Conversely, values of zero (0.000) indicate that the relevant country fell below the average for that criterion, thereby failing to generate any "positive" score.

Table 14. EDAS negative distance values from the mean

Code/Criteria	SUI	CO_2	Gini	API	EPI	SDG	HDI	WGI
A1	0,000	1,221	0,000	0,375	0,000	0,000	0,000	0,000
A2	0,102	0,103	0,000	0,405	0,000	0,000	0,000	0,000
A3	0,000	0,000	0,472	0,000	0,039	0,037	0,102	0,535
A4	0,279	1,129	0,000	0,000	0,000	0,000	0,000	0,000
A5	0,395	0,000	0,227	0,000	0,100	0,000	0,000	0,043
A6	0,000	0,317	0,027	0,227	0,358	0,030	0,090	0,394
A7	0,132	0,000	0,538	0,000	0,098	0,081	0,100	0,614
A8	0,084	0,000	0,000	0,176	0,000	0,000	0,000	0,000
A9	0,016	0,072	0,000	0,105	0,000	0,000	0,000	0,000
A10	0,012	0,000	0,000	0,000	0,000	0,000	0,000	0,260
A11	0,000	0,000	0,000	0,000	0,499	0,128	0,218	0,273
A12	0,318	0,000	0,000	0,354	0,000	0,000	0,000	0,000
A13	0,000	0,000	0,000	0,110	0,000	0,000	0,000	0,167
A14	0,140	0,210	0,000	0,553	0,000	0,000	0,000	0,000
A15	0,000	0,000	0,241	0,339	0,198	0,074	0,099	0,798
A16	0,096	0,000	0,000	0,380	0,000	0,000	0,000	0,000
A17	0,213	0,000	0,000	0,000	0,537	0,256	0,379	0,826
A18	0,000	0,823	0,000	0,822	0,153	0,031	0,050	0,999
A19	0,091	0,348	0,241	0,944	0,039	0,085	0,000	0,000
A20	0,000	0,746	0,000	0,817	0,082	0,000	0,000	0,000
A21	0,291	0,000	0,000	0,034	0,000	0,000	0,000	0,000
A22	0,168	0,000	0,000	0,000	0,000	0,000	0,000	0,000
A23	0,000	0,000	0,000	0,380	0,000	0,000	0,000	0,000
A24	0,000	1,191	0,193	0,446	0,000	0,018	0,000	0,000
A25	0,000	0,000	0,030	0,000	0,554	0,044	0,125	0,417

Table 14 measures instances where countries fall behind average performance, representing "weaknesses" in terms of sustainability. An examination of the table reveals that countries such as the USA (A24) and Russia (A18) exhibit high negative distance values, particularly in the CO_2 emissions and Sustainability Uncertainty (SUI) columns; this implies that these nations perform significantly worse than the average, resulting in a loss of points within the system. For instance, the value of 0.823 in A18's CO_2 column serves as evidence of how negatively it diverges from the mean regarding emissions.

Table 15. EDAS weighting of positive distances from the mean

Code/Criteria	SUI	CO_2	Gini	API	EPI	SDG	HDI	WGI	SPi	N-SPi
A1	0,022	0,000	0,004	0,000	0,015	0,001	0,009	0,085	0,135	0,291
A2	0,000	0,000	0,026	0,000	0,021	0,004	0,008	0,061	0,120	0,259
A3	0,055	0,100	0,000	0,165	0,000	0,000	0,000	0,000	0,320	0,690
A4	0,000	0,000	0,012	0,025	0,011	0,003	0,007	0,080	0,138	0,297
A5	0,000	0,062	0,000	0,028	0,000	0,002	0,000	0,000	0,092	0,198
A6	0,007	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,007	0,015
A7	0,000	0,114	0,000	0,062	0,000	0,000	0,000	0,000	0,176	0,380
A8	0,000	0,058	0,010	0,000	0,022	0,006	0,005	0,049	0,150	0,323
A9	0,000	0,000	0,008	0,000	0,036	0,007	0,009	0,088	0,147	0,317
A10	0,000	0,034	0,005	0,011	0,022	0,003	0,003	0,000	0,078	0,169
A11	0,053	0,105	0,030	0,094	0,000	0,000	0,000	0,000	0,282	0,607
A12	0,000	0,001	0,019	0,000	0,020	0,002	0,008	0,097	0,145	0,313
A13	0,009	0,031	0,002	0,000	0,009	0,003	0,004	0,000	0,060	0,130
A14	0,000	0,000	0,009	0,000	0,011	0,003	0,005	0,086	0,115	0,248
A15	0,052	0,072	0,000	0,000	0,000	0,000	0,000	0,000	0,123	0,266
A16	0,000	0,001	0,029	0,000	0,022	0,003	0,008	0,097	0,160	0,346
A17	0,000	0,136	0,017	0,135	0,000	0,000	0,000	0,000	0,288	0,620
A18	0,075	0,000	0,006	0,000	0,000	0,000	0,000	0,000	0,081	0,175
A19	0,000	0,000	0,000	0,000	0,000	0,000	0,007	0,109	0,116	0,251
A20	0,003	0,000	0,007	0,000	0,000	0,002	0,006	0,056	0,074	0,160
A21	0,000	0,048	0,005	0,000	0,016	0,004	0,004	0,012	0,090	0,194
A22	0,000	0,072	0,018	0,235	0,028	0,009	0,009	0,093	0,464	1,000
A23	0,022	0,048	0,008	0,000	0,032	0,005	0,007	0,072	0,194	0,418
A24	0,006	0,000	0,000	0,000	0,004	0,000	0,007	0,065	0,081	0,174
A25	0,054	0,072	0,000	0,028	0,000	0,000	0,000	0,000	0,153	0,331

At this stage, the countries' positive distances (PDA) are multiplied by the CRITIC weights to transform them into a total "success score" (SPi). A review of the SPi column reveals that Sweden (A22) achieved the highest score of 0.464 and distinguished itself markedly from other countries by receiving a full score (1.000) in the normalized value (N-SPi). Table 15 elucidates which countries have best optimized their strengths (i.e., success in highly weighted criteria).

Table 16 presents the weighted sum of countries' disadvantages (SNi), where the objective is to minimize this value. Russia (A18) exhibits the highest SNi value at 0.446, making it the most "penalized" country in terms of performance. Conversely, the notably low SNi values for countries such as the UK (A23) and Sweden (A22) (0.046 and 0.026, respectively) indicate that these nations possess very few weaknesses or that their weaknesses are concentrated in criteria with lower weights.

Representing the final output of the entire analysis process, Table 17 presents the overall sustainability ranking derived from the synthesis of countries' Positive and Negative distances (ASi score). Sweden (A22) ranks first with a remarkably high score of 0.971, followed by the UK (A23) and India (A11). At the bottom of the list are Russia (A18) with 0.088 points and China (A6) with 0.279 points; this result summarizes how high emissions and uncertainty can overshadow achievements in other areas, thereby diminishing overall performance.

Table 16. EDAS weighting of negative distances from the mean

Code/Criteria	SUI	CO_2	Gini	API	EPI	SDG	HDI	WGI	SNi	N-SNi
A1	0,000	0,189	0,000	0,045	0,000	0,000	0,000	0,000	0,234	0,475
A2	0,016	0,016	0,000	0,049	0,000	0,000	0,000	0,000	0,081	0,819
A3	0,000	0,000	0,052	0,000	0,004	0,003	0,009	0,106	0,173	0,612
A4	0,043	0,175	0,000	0,000	0,000	0,000	0,000	0,000	0,217	0,513
A5	0,060	0,000	0,025	0,000	0,010	0,000	0,000	0,008	0,104	0,768
A6	0,000	0,049	0,003	0,028	0,036	0,002	0,008	0,078	0,204	0,543
A7	0,020	0,000	0,059	0,000	0,010	0,006	0,009	0,121	0,225	0,496
A8	0,013	0,000	0,000	0,021	0,000	0,000	0,000	0,000	0,034	0,923
A9	0,002	0,011	0,000	0,013	0,000	0,000	0,000	0,000	0,026	0,941
A10	0,002	0,000	0,000	0,000	0,000	0,000	0,000	0,051	0,053	0,881
A11	0,000	0,000	0,000	0,000	0,050	0,009	0,020	0,054	0,134	0,701
A12	0,049	0,000	0,000	0,043	0,000	0,000	0,000	0,000	0,091	0,795
A13	0,000	0,000	0,000	0,013	0,000	0,000	0,000	0,033	0,046	0,896
A14	0,021	0,033	0,000	0,067	0,000	0,000	0,000	0,000	0,121	0,729
A15	0,000	0,000	0,026	0,041	0,020	0,005	0,009	0,157	0,259	0,419
A16	0,015	0,000	0,000	0,046	0,000	0,000	0,000	0,000	0,061	0,864
A17	0,033	0,000	0,000	0,000	0,054	0,018	0,035	0,163	0,303	0,321
A18	0,000	0,127	0,000	0,100	0,015	0,002	0,005	0,197	0,446	0,000
A19	0,014	0,054	0,026	0,114	0,004	0,006	0,000	0,000	0,218	0,511
A20	0,000	0,116	0,000	0,099	0,008	0,000	0,000	0,000	0,223	0,501
A21	0,044	0,000	0,000	0,004	0,000	0,000	0,000	0,000	0,049	0,891
A22	0,026	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,026	0,943
A23	0,000	0,000	0,000	0,046	0,000	0,000	0,000	0,000	0,046	0,897
A24	0,000	0,184	0,021	0,054	0,000	0,001	0,000	0,000	0,261	0,416
A25	0,000	0,000	0,003	0,000	0,056	0,003	0,012	0,082	0,156	0,650

Table 17. EDAS final ranking

Code	Country	ASi	Ranking	Code	Country	ASi	Ranking
A1	Australia	0,383	19	**A13**	Italy	0,513	12
A2	Belgium	0,539	10	**A14**	Japan	0,488	14
A3	Brazil	0,651	4	**A15**	Mexico	0,342	21
A4	Canada	0,405	18	**A16**	Netherlands	0,605	7
A5	Chile	0,483	15	**A17**	Pakistan	0,471	16
A6	China	0,279	24	**A18**	Russia	0,088	25
A7	Colombia	0,438	17	**A19**	Singapore	0,381	20
A8	France	0,623	6	**A20**	S Korea	0,331	22
A9	Germany	0,629	5	**A21**	Spain	0,543	9
A10	Greece	0,525	11	**A22**	Sweden	0,971	1
A11	India	0,654	3	**A23**	UK	0,658	2
A12	Ireland	0,554	8	**A24**	US	0,295	23
				A25	Vietnam	0,490	13

4.1. Sensitivity analysis

In this study, the Monte Carlo simulation method was applied to verify the robustness of the proposed EDAS model and to measure the resilience of the obtained country rankings against uncertainties in the criterion weights. Unlike classical one-dimensional sensitivity analyses, this study simultaneously and randomly manipulated all criterion weights to explore a more comprehensive uncertainty space. The simulation and analysis process was performed using a computational algorithm developed in the Python programming language. In the algorithmic infrastructure, NumPy and Pandas libraries were used for multidimensional matrix operations and iterative calculations of the EDAS method. In contrast, Matplotlib and Seaborn libraries were used for statistical visualization (box plots, heat maps, and scatter diagrams) of the large data set obtained. During the analysis process, a random perturbation of ±20% was applied to the base weight coefficients (w_j) determined by the CRITIC method, and 10,000 different scenarios were derived in accordance with a uniform distribution.

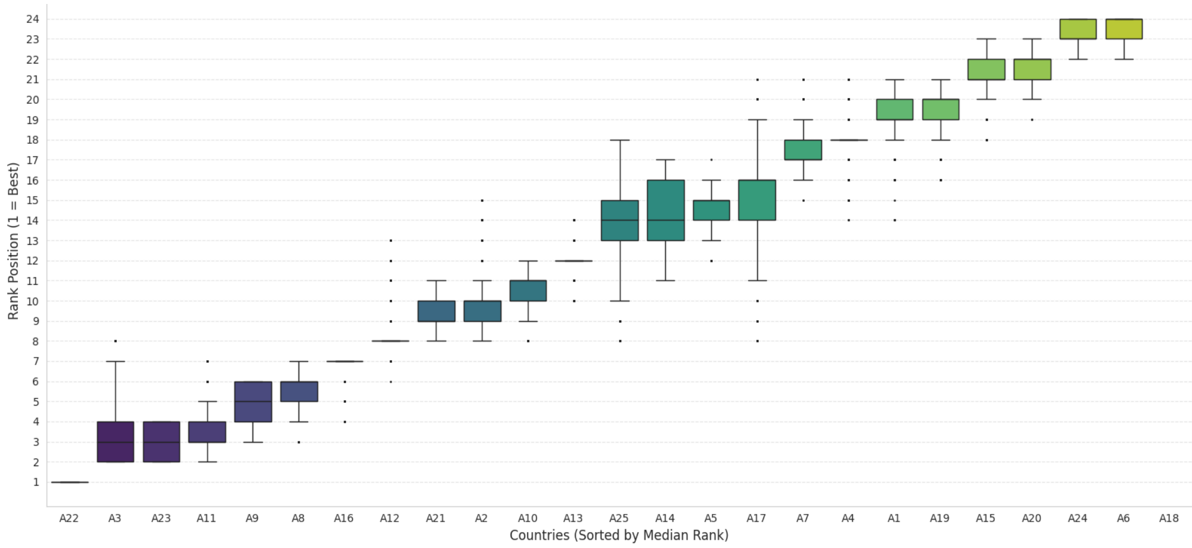

Figure 1. Country-based ranking distribution (cumulative bar chart)

The stacked bar Figure 1 presents the cumulative distribution of rankings achieved by each country throughout the simulation scenarios. The concentration of columns for countries like A22 and A3 on the left side of the graph in a single color or limited color blocks indicates high performance stability for these countries. However, as one moves towards the middle section (especially A12, A10, A25), the fragmented structure of columns with numerous different colors becomes noticeable, revealing that the rankings of these countries fluctuate over a wide range depending on weighting changes, thereby increasing ranking uncertainty. A18, located on the far right, consistently ranks low (yellow blocks), indicating negative stability.

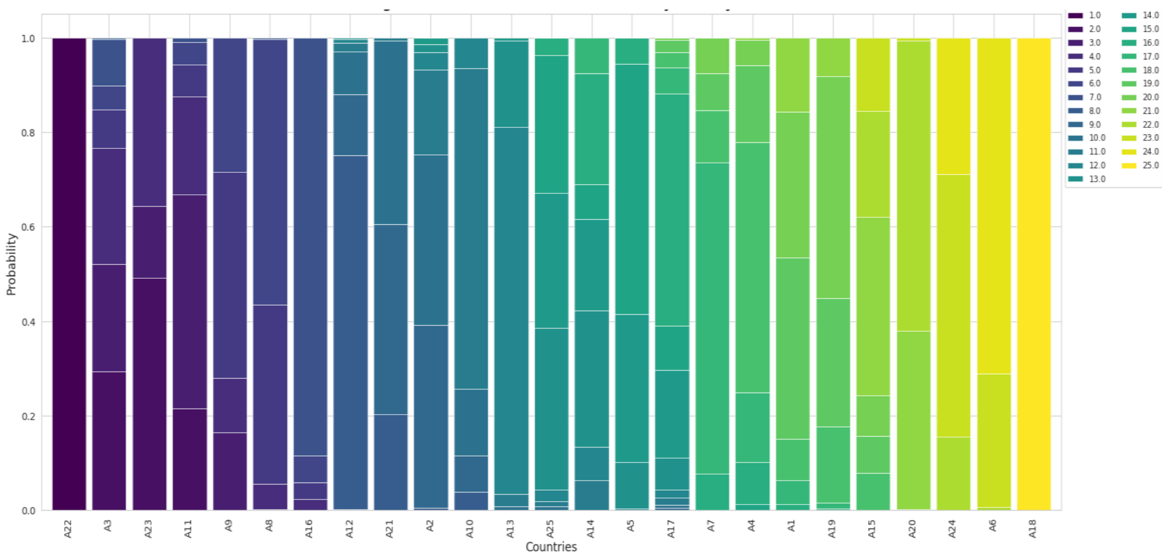

Figure 2. Heatmap of ranking probabilities

Heatmap presented in Figure 2 visualizes the probability of countries achieving specific ranking positions as a result of Monte Carlo simulation. Darker cells indicate a higher frequency (probability) of the country being in that position. For example, the intense dark color in the first-rank column for country A22 demonstrates that it maintains its top position regardless of weighting changes, and the results are quite robust for this country. In contrast, the color distribution of mid-ranked countries, such as A14 and A5, is spread over a wide area on the horizontal axis, and the colors become more faded, indicating that these countries' rankings are more sensitive to criterion weightings and that assigning a precise ranking is challenging.

Figure 3. Performance vs. stability analysis (scatter plot)

Figure 3 shows the scatter plot analyzes the relationship between countries' "average performance" (X-axis) and "ranking stability" (Y-axis) in strategic terms. A22, located in the ideal position in the lower left corner, is the most successful and reliable country in the system, as it has both the best average ranking and a standard deviation close to zero. A14 and A17, located at the top of the graph (above 1.50 on the Y-axis), stand out as the countries with the highest standard deviation values despite their average performance, indicating that they have the most fragile (volatile) structure against weight changes. This graph is critical because it shows decision-makers not only who is first, but also whose position is "guaranteed."

The Monte Carlo sensitivity analysis (10,000 scenarios and ±20% random variation in weights) applied to test the validity of the ranking obtained using the EDAS method demonstrated that the proposed model possesses a high level of robustness. As a result of the analysis, country A22 maintained its leadership across all weighting scenarios, demonstrating the undisputed best performance, while country A18 remained in last place with similar stability. Despite this reliable structure observed at the top and bottom of the ranking, it was found that the standard deviation increased in the middle ranks (particularly in countries such as A14 and A17) and that the ranking positions varied according to the criteria preferences; This situation proves that the performance of the countries concerned is dependent on specific criteria, but that the general ranking hierarchy (based on upper, middle, and lower groups) remains intact.

5. Conclusion

This study aims to contribute to the literature by evaluating countries' sustainability performance not only through established environmental, social, and governance (ESG) indicators but also by including the concept of "uncertainty", which directly affects the feasibility of these policies. The Sustainability Uncertainty Index (SUI/ESGUI) integrates the HDI and the WGI into a multidimensional framework that assesses sustainability not only in physical or economic terms but also in terms of human development and the rule of law. HDI, and WGI. This multidimensional framework demonstrates that sustainability is not merely a physical or economic output but also a matter of institutional predictability. The findings of the CRITIC weighting method, applied based on the internal information structure of the data set, reveal that the Rule of Law and SUI are the criteria with the highest discriminatory power in distinguishing countries' performance. This statistically confirms that the elements of "institutional trust" and "policy stability," which are often overlooked in sustainability discussions, are in fact variables that are just as decisive as carbon emissions.

When examining the performance ranking conducted using the EDAS method, Sweden (A22) stands out as the leader, clearly distinguishing itself from other countries due to its low uncertainty level and superior performance in environmental and social indicators. The fact that the United Kingdom and India follow Sweden demonstrates that the model's logic of "positive deviation from the average solution" can bend the traditional hierarchy between developed and developing countries by focusing on specific areas of success (such as India's low per capita emissions or renewable energy potential). In contrast, it is noteworthy that Russia, China, and the United States, despite being global economic powers, rank near the bottom of the list. In particular, Russia's highest negative distance score is a concrete demonstration of how high carbon emissions, deepening income inequality, and a weak legal system, combined with high policy uncertainty, can undermine a country's sustainability record. This result reveals that economic size or industrial capacity alone is not sufficient for building a sustainable future; instead, governance weaknesses can turn this capacity into a "punitive" factor.

The Monte Carlo simulation applied to test the reliability of the obtained ranking has confirmed the structural stability of the proposed model. The sensitivity analysis conducted under ten thousand different scenarios showed that Sweden's leadership and Russia's last place remained unchanged despite random changes in weight coefficients. However, the study also revealed that the ranking positions of countries in the middle range (such as Japan or Chile) exhibited a more sensitive and variable structure in response to criterion preferences. This finding suggests that countries in the "fragile" or "transitional" performance group should adopt a balanced improvement policy encompassing all criteria, rather than focusing their sustainability strategies on a single area (such as energy alone).

From the perspective of policymakers, the most fundamental recommendation offered by this study is the necessity to redefine sustainability strategies around the axis of "uncertainty management". Findings indicate that countries that enhance predictability in environmental regulations, avoid sudden policy changes, and establish the rule of law gain a competitive advantage in the green transition process. Therefore, "decarbonization" goals should be pursued not only as a technological infrastructure investment but also in tandem with improving institutional quality and ensuring social justice (as measured by the Gini and HDI indices). For developing countries in particular, this study demonstrates that minimizing institutional uncertainty, in addition to reducing emissions, is a low-cost yet high-impact lever for achieving top rankings in the global sustainability league.

This study has several limitations, which also present significant opportunities for future research. First, the analysis was conducted with a limited set of criteria consisting of 25 selected countries and eight indicators (SUI, CO_2, Gini, API, EPI, SDG, HDI, and WGI), largely representative of the year 2023. Therefore, expanding both the country coverage and the diversity of indicators would increase the generalizability and explanatory power of the findings. Furthermore, the study presents a cross-sectional and static ranking based on the CRITIC and EDAS methods; it does not directly examine transformations over time, structural breaks, or the effects of policy interventions. Therefore, future research is recommended to incorporate dynamic MCDM approaches with panel datasets covering longer periods, combined with econometric models focusing on causal relationships (e.g., panel regressions using EDAS scores as dependent or independent 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.

Acknowledgments

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

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