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ORIGINAL PAPER

Artificial intelligence predictor of circular economy actions in the social economy

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Abstract
Corporate social responsibility (CSR) encompasses companies' voluntary actions that integrate economic, social, and environmental concerns into their operations. Concurrently, the circular economy (CE) has emerged as a transformative organizational paradigm that replaces the traditional linear "take-make-dispose" model with a regenerative system to minimize waste and optimize resource use. This study harnessed artificial intelligence (AI) as a tool for predicting circular practices and exploring how CSRI can indicate organizations' orientation toward CE principles. To this end, the research conducted partial least squares (PLS) structural equation modeling using SmartPLS software to analyze a sample of 129 social economy organizations in Spain. The findings confirm the validity of the proposed causal relationships and demonstrate the potential of AI-assisted analytical approaches for modeling complex constructs. Overall, the results contribute to the literature on the intersection of CSR and CE by providing theoretical and practical insights into how digital technologies can facilitate the transition from linear to circular business models in the social economy sector.

Keywords Corporate social responsibility · Information · Circular economy · Artificial intelligence · Social economy · Structural equation modeling

JEL Classification M10 · M14

1 Introduction

Corporate social responsibility (CSR) corresponds to a set of actions developed voluntarily by companies, in three classic dimensions: economic, social, and environmental. Directly linked to CSR, the disclosure process carried out by companies known

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as CSR reporting (CSRR) is extremely important. CSRR refers to the structured, systematic, and generally periodic (e.g., annual) presentation of CSR information (CSRI), which follow recognized guidelines. For instance, this communication may include publications on the corporate website about social projects, press releases on volunteering or sustainability initiatives, social media posts about ecological actions, sustainability reports that meet Global Reporting Initiative (GRI) standards, non-financial reports, or sections in annual reports that mention responsible practices. CSRR uses defined methodologies and metrics to ensure comparability and transparency. This kind of reporting can also involve external verification or audits and have a more formal, accountability-oriented nature.

Once considered a voluntary strategy, CSRR is increasingly becoming a regulatory requirement, especially in European contexts. The European Union's (EU) Corporate Sustainability Reporting Directive established mandatory disclosure obligations operationalized through the European Sustainability Reporting Standards. Recent proposals such as the OMNIBUS 1 and OMNIBUS 2 have further refined these requirements to ensure the comparability and reliability of sustainability disclosure (European Commission, 2022). CSRR has numerous potential features that reinforce the purpose of this type of communication (Busco et al. 2020; Vieira and Radonjic 2020; García-Meca and Martínez-Ferrero 2021). The associated practices can also help organizations identify new opportunities in potential markets, develop more socially responsible initiatives, and focus on new tactics such as the circular economy (CE) (Liu et al. 2019; Gallardo-Vázquez et al. 2024a).

The CE has emerged as a new organizational strategy based on the development of circular production models as opposed to traditional linear production ones. The CE evolved from waste management approaches (i.e., CE 1.0) that integrated value creation strategies (i.e., CE 3.0), becoming increasingly important for business model innovation and strategic management (Reike et al. 2018). The Ellen MacArthur Foundation (2015) has promoted this systemic approach by emphasizing the economic and business rationale for accelerating the transition into circularity. Embedding the CE into business management requires redesigning products and processes, transforming value chains, and integrating circular principles into core business decisions. This new perspective motivates companies to reuse by-products and waste and reintroduce them into the value chain to achieve additional reductions (Guranathne et al. 2021; Marco-Fondevila et al. 2021; Llena-Macurulla et al. 2023).

The literature confirms that a link exists between CSR—or some of its dimensions or those of CSRR—and the CE. For example, Gallardo-Vázquez, Herrador-Alcaide, and Matin (2024) showed how CSR can guide the CE. The cited authors applied various theories to clarify how CSR practices had a significant positive influence on CE orientation in two independent samples of small and medium-sized enterprises (SMEs) in Spain. Gallardo-Vázquez, Herrador-Alcaide, and Matin's (2024) results additionally supported proposals about the creation of stakeholder value. Other researchers have focused on how CSRR provides economic, social, and environmental indicators of alignment with the CE, suggesting an integration of the three topics under study (i.e., CSR, CE, and CSRR) (Rossi et al. 2020; Morea et al. 2021; Falkenberg et al. 2023). In this way, comparable transparent and inclusive informa-

tion can be compiled in sustainability reports, and observations of CE practices could be conducted (Abeysekera 2022; Damiano and Di Maria 2024).

The present research focused on CSR and the relative importance of CE strategies, relying on artificial intelligence (AI) to predict companies' circular initiatives. AI can play a crucial role in understanding and strengthening this connection. First, large volumes of data can be collected from and analyzed in sustainability reports by using AI to identify trends and correlations between CSR and CE practices (Lachuer and Ben Jabeur 2022). These machine learning techniques could expedite the development of predictive models that anticipate how CSR policies may affect the implementation of CE strategies (Sohaib et al. 2020).

Second, AI can improve the transparency and accountability derived from CSRR and can contribute to more accurate sustainability reporting in order to facilitate the communication of CE activities to stakeholders (Hauer et al. 2023). AI tools can evaluate and control the social and environmental impacts of operations in real time, making the adjustment of CSR and CE strategies easier. Last, AI is able to identify innovation opportunities leading to greater sustainability, reveal gaps in current practices, and suggest improvements based on historical data and emerging trends (Kim et al., 2022). The cited authors applied AI to social innovations specifically with regard to uncertainties and conflicts existing in business behaviors.

The current study was conducted to fill a gap in the literature, namely, to provide a clearer explanation of the relationship between CSR and the CE based on sustainability information and the existing barriers to the CE. Given this goal, the first objective was to identify organizations' orientation toward the CE via their CSRI, in this case combining an explanatory approach—to understand the underlying relationships among the variables—with a predictive model—to assess whether specific variables indicate a tendency to a CE orientation. CSRI was defined as firms' actions, policies, or outcomes related to social, environmental, or ethical issues. This information may refer to social projects, volunteering activities, and ecological initiatives—in short, responsible practices. These initiatives can be occasional, non-standardized, or only informally integrated into companies' overall strategy.

The second objective was to build a CE predictive model based on CSRR by using partial least squares (PLS) structural equation modeling (SEM) and AI tools. CSRI was positioned as the starting element and linked to the implementation of CSR actions (CSRAs). The latter defines the barriers and incentives to the CE (BICE) that affect organizations' ability to achieve a CE orientation. The following research questions were addressed:

- ***RQ1***: Are CSR and the CE interconnected concepts?
- ***RQ2***: Can CSRI contribute to the implementation of CSRAs?
- ***RQ3***: Can the implementation of CSRAs determine the BICE?
- ***RQ4***: Can the identification of BICE facilitate the implementation of CE strategies?
- ***RQ5***: Can CSRI condition CE strategies?
- ***RQ6***: Can AI contribute to the definition of a predictive model in this context?

To this end, the study developed structural equation models based on variances in variables using PLS-SEM and a sample of 129 social economy entities in Spain. Favorable results were obtained for the different causal relationships proposed.

The findings offer three significant contributions to the literature on CSR and the CE, as well as highlighting the role of AI in defining circular actions based on CSRI. First, this research contributes to the body of work on the integration of CSR and the CE, demonstrating how CSR practices can guide organizations toward CE strategies. Empirical evidence was found that CSR activities positively influence the adoption of CE practices, thereby advancing the development of sustainable business models. This result aligns with the literature that suggests a strong connection between CSR and CE initiatives (Gallardo-Vázquez et al. 2024a).

Second, the current study sought to expand the prior research on predictive modeling with AI. AI techniques were used to construct predictive models of the impact of CSR policies on CE implementations. This novel approach not only enhances the understanding of CSR–CE dynamics but also provides a practical tool for organizations seeking to forecast the outcomes of their CSR initiatives in terms of circular actions. These findings add to the literature on the use of AI in sustainability reporting and prediction (Lachuer and Ben Jabeur 2022).

Last, the present research enriches the literature by identifying and analyzing BICE, offering insights into how organizations can overcome challenges and leverage opportunities to implement circular strategies. These results contribute to the broader discussion on the practical obstacles to and enablers of CE adoption, as reported by Kirchherr et al. (2018) and Guerra and Leite (2021). The originality of the current work lies in its integrative model, which links CSRI with the implementation of CE strategies and thus highlights the predictive, transformative role of CSR in sustainability transitions.

From a theoretical standpoint, this study adopted an explanatory perspective based on the proposed causal relationships between CSRI, the implementation of CSRAs, the identification of BICE, and CE orientation. These links were grounded in the literature and defined to explain how and why CSR-related information and practices contribute to circular strategies. Reflecting recent methodological advances (Hair et al. 2024), the present research also explicitly incorporated a predictive perspective to assess the proposed model's ability to anticipate CE orientation based on observable CSRI. In this sense, the explanatory and predictive objectives were treated as complementary rather than competing goals.

The conceptual framework and hypotheses were theory-driven and explanatory in nature, but the empirically robust analyses leveraged the prediction-oriented techniques to evaluate the model's out-of-sample performance. This dual approach was adopted in response to recent calls in the methodological literature for researchers to distinguish more clearly between explanation and prediction in SEM, especially in sustainability and management contexts (Valls Martínez et al. 2025).

2 Theoretical framework

2.1 AI and predictive models

PLS-SEM has increasingly been integrated with AI—more specifically artificial neural networks (ANNs)—to form a significant emerging area of research especially interested in technology acceptance (Yin et al. 2003). ANNs enhance PLS-SEM by providing more accurate, profound results, confirming PLS-SEM conclusions, and offering high predictive accuracy in models of both linear and complex nonlinear relationships (Sohaib et al. 2020). This integrated methodology enables the evaluation of the relative influence of predictor variables, which is particularly useful in technology acceptance research (Yoon et al. 1994). In addition, ANNs complement PLS-SEM by overcoming its limitations in terms of nonlinear relationships between variables and determine the relative importance of each factor. Finally, importance-performance map analysis (IPMA) is used in conjunction with PLS-SEM and ANNs to provide a detailed understanding of the importance and performance of each factor in technology acceptance (Yoon et al. 1994).

Recent research has highlighted the economic and managerial implications of AI adoption in various sectors, providing valuable insights that can be extrapolated to the sustainability and CE fields. For instance, Hernández-Tamurejo et al. (2025) analyzed the market dynamics and investment drivers of AI adoption in online travel agencies and identified scalability and data governance as key success factors. Roppelt et al. (2025), in turn, conducted empirical research on the organizational capabilities and governance mechanisms required for the effective integration of AI into the healthcare sector. The cited study underlined that, beyond technical performance, successful AI adoption depends on organizational readiness, strategic alignment, and value creation logic—three aspects that are equally important when applying AI to accelerate CE transitions.

Besides their role in enhancing PLS-SEM, ANNs have demonstrated their versatility and efficacy in varied research fields. These networks can support expert system development by combining this type of system with rule-based ones to form high-performance knowledge-based networks that facilitate managerial decision making. In control applications such as shunt active power filters, ANNs' parallel computing and high learning capabilities offer significant advantages in performance and implementation (Qasim and Khadkikar 2014). ANNs are also able to model processes without in-depth knowledge of underlying physical and chemical rules, which makes these networks a powerful tool in operations such as membrane separation because ANNs can efficiently estimate performance characteristics (Asghari et al. 2020).

When used alongside PLS-SEM, ANNs can corroborate SEM-based findings and estimate the relative importance of determinants in consumer behavior studies (e.g., m-wallet adoption), as well as strengthening findings in behavioral intention studies (Hidayat-ur-Rehman et al. 2022). In addition, ANNs are applied in analyses of complex structures to optimize sensor and actuator placement, thereby reducing costs and accommodating inaccessible points—as validated by both finite element method models and real data (Savastano et al. 1994). ANNs can further be combined with autoregressive integrated moving average models in time series to enhance fore-

casting accuracy, especially when higher accuracy is necessary (Khashei and Bijari 2010).

2.2 CSRI and implementation of CSRAs

The relationship between these two aspects of CSR forms a cyclical process of communication and action within companies. CSRI is an important asset that can reveal opportunities in potential markets (Liu et al. 2019; Gallardo-Vázquez and Valdez-Juárez 2022). Gallardo-Vázquez and Valdez-Juárez (2022) also showed that CSRI has a direct positive influence on the development of social, economic, and environmental initiatives. The implementation of CSRAs, in turn, allows organizations to identify areas needing improvement and opportunities for initiatives that can be publicized in sustainability reports. As more CSRAs are implemented, more information is generated about the impact of these actions, which feeds a cycle of continuous CSR improvement.

CSRI thus functions as a powerful communication tool for businesses (Lozano et al. 2016; Busco et al. 2020; Vieira and Radonjic 2020; García-Meca and Martínez-Ferrero 2021), which involves collecting, evaluating, and disseminating information about organizations' social, environmental, and ethical practices and policies. CSRI is a necessary resource for companies that seek to develop CSR activities that benefit different interest groups (Gallardo-Vázquez and Valdez-Juárez 2022). This information provides companies with a database on their social and environmental performance in the form of reports about impacts on their community, the environment, employees, and other interested parties. These data support decisions about how to improve CSR performance (Palacios-Manzano et al. 2024). Effective CSRR delineates the intricate nexus between environmental and social management, intertwining these areas with business strategies and competitive tactics and holistically integrating economic, social, and environmental information (Mook 2006; Schaltegger and Wagner 2006). Businesses must prepare uniform, comparable sustainability data and ensure they are disseminated through sustainability reports (Abeysekera 2022).

The literature reflects a significant growth in sustainability reports over the past two decades (Bray and Ridehalgh 2020; Threlfall et al. 2020). Studies have also detected a progressive movement from social and environmental reports (Cormier and Gordon 2001; Clarkson et al. 2008; Fifka 2012) to more inclusive and transparent CSR reports or sustainability reports (Damiano and Di Maria 2024).

Many justifications are given for sustainability reporting, which are intertwined with the reasons for implementing CSRAs. First, sustainable investments now include a comprehensive spectrum of information on investment in capital markets, including both financial and non-financial aspects, to help investors make informed decisions about capital markets (Busco et al. 2020; Ernst and Young 2020; García-Meca and Martínez-Ferrero 2021). Financiers look for benefits and lower costs for their interest groups. These requirements arise out of investors' quest for shareholder wealth maximization, alongside risk mitigation and legitimacy within their sectors.

Second, sustainability information facilitates and improves stakeholder engagement, enhancing the relationships between these groups while ensuring transparency in corporate affairs (Lozano et al. 2016; Vieira and Radonjic 2020). By aligning their

sustainability reporting with CSRAs, businesses both meet stakeholders' expectations and foster long-term sustainability and resilience in ever-evolving marketplaces. Last, Blanco-Zaitegi et al. (2022) found that, in environmental accounting, CSRI has emerged as a pivotal nexus, that is, a unifying force encompassing varied themes (e.g., biodiversity accounting, impact mitigation, and biodiversity compensation), all of which promote the implementation of CSRAs.

In the economic dimension, CSRI conveys companies' maximization of shareholder value and financial viability (Turker 2009; Crifo and Forge 2012), thereby reflecting their CSRAs. Using AI can facilitate the processing of massive data and thus predict which business models will promote organizational profitability and which new actions should be implemented. In this context, CSRI provides guidance for companies seeking to enter new markets, implement new technology, transform operations, and create more valuable efficiency measures through proactive production and sales strategies (Mather 2020; Obrenovic et al. 2020). This information supports the commercial operations needed to implement CSRAs or requests for financing to undertake them (Larcker et al. 2020; Eiadat 2023). AI is concurrently able to carry out analyses of prospective investments and financing data that help companies to sustain their level of business activity and even prosper (Eiadat 2023).

In the social dimension, CSRI provides data on health issues and local communities' efforts to contribute to regional development. Employees can be associated with social and economic aspects such as community relationships, growth potential, and value creation (López-Cózar-Navarro and Benito-Hernández 2017). Liang and Yoon (2023) noted that workers pay attention to more than just salaries since how company CSR is perceived by employees affects their subjective welfare. The cited authors further examined organizational identification as an intermediary mechanism through which workers perceive their own well-being. In short, CSR affects the degree to which employees focus on their happiness at work, quality of life, and psychological well-being (Castro-Casal et al. 2024).

AI can also configure personalized professional development plans, defining training programs that consolidate employees' skills and competencies, align growth opportunities with their interests and needs, and match workers with suitable mentors. In addition, AI tools are able to analyze employee sentiment based on surveys or other data in order to identify areas to improve in work environments, define automatic recognition systems of employees' achievements and contributions, and thus ensure their work is appreciated and receives fair and timely recognition (Maity 2019; Rukadikar and Khandelwal 2023).

Analyses of CSR from a customer perspective have revealed that successful companies are concerned about not only increasing their sales and obtaining greater profitability but also enhancing and emphasizing their social impact and returning value to society at large. Customer trust and loyalty are thus determined by subjective impressions of specific aspects of companies' social responsibility (Barlas et al. 2023). AI can strengthen consumer confidence and fidelity by improving customer service through 24-h virtual assistants that can resolve queries and problems quickly and efficiently. AI tools are able to carry out personalized analysis of customers' behaviors and preferences to improve their experience, undertake sentiment analysis, and obtain feedback identifying areas needing improvement and offering opportuni-

ties. Other functions include defining smart loyalty programs that reward customers for their loyalty and personalize marketing communication to increase the effectiveness of campaigns and strengthen customer relationships (Rukadikar and Khandelwal 2023).

In the environmental dimension, CSRI broadcasts organizations' green agendas (Jabbour and Renwick 2020; Hendiani et al. 2022) and prioritization of initiatives such as pollution reduction, waste elimination, use of renewable materials (Agyabeng-Mensah et al. 2020), and adoption of green technologies (You et al. 2020). AI can then evaluate the results achieved via the CSRI for each initiative and predict the benefits of continuing in the same direction or taking new CSRAs.

Innovative companies' CSRI is thus a key factor that generates trust, legitimacy, and financial benefits (Ghouri et al. 2019), while AI can predict whether business reputations will grow based on companies' efforts to improve (Konadu et al. 2020). The results detailed in sustainability reports combine with AI support to ascertain the desirability of entering new markets (Konadu et al. 2020) and attracting valuable, rare talents (Agyabeng-Mensah et al. 2020). Figure 1 presents the relationship between CSRI and implementation of CSRAs with the aid of AI tools.

In summary, CSRR and the implementation of CSRAs are interconnected and mutually reinforcing throughout the process of publicizing sustainable and ethical business practices. The first hypothesis defined for the present study addressed RQ2, namely, the development of a better understanding of the link between CSRI and implementation of CSRAs:

Hypothesis 1 (H1) *Access to CSRI will directly and positively determine the implementation of CSRAs.*

2.3 Implementation of CSRAs and BICE

The CE has caught the attention of many researchers in recent years (D'Amato et al. 2017; Kirchherr et al. 2018; Acquier et al. 2024). Within the related fields, significant progress has been made in studying barriers to circular practices (Shahbazi et al. 2016; Kirchherr et al. 2018; García-Quevedo et al. 2020; Arena et al. 2021; Gedam et al. 2021; Grafström and Aasma 2021). Obstacles can arise from five distinct origins: cultural, market, regulatory, financial, and technological factors (De Jesus et al. 2018; Hart et al. 2019; García-Quevedo et al. 2020; Gedam et al. 2021).

Cultural barriers to the CE refer to the lack of consumer interest and awareness and resistance within company culture, which hinder the adoption of circular practices and the integration of CE concepts into business strategies and operations. These obstacles can be seen in consumers' preference for new products, companies' lack of commitment to the CE in their corporate culture, and a reluctance to move away from traditional linear business models (De Jesus et al. 2018; Kirchherr et al. 2018; Singh et al. 2018).

Market barriers in the CE hinder transitions through factors such as low priced virgin materials and high cost circular business models. These challenges make circular products less competitive and deter firms from investing in circular initiatives. While often overlooked in the literature, market barriers emerge as significant challenges

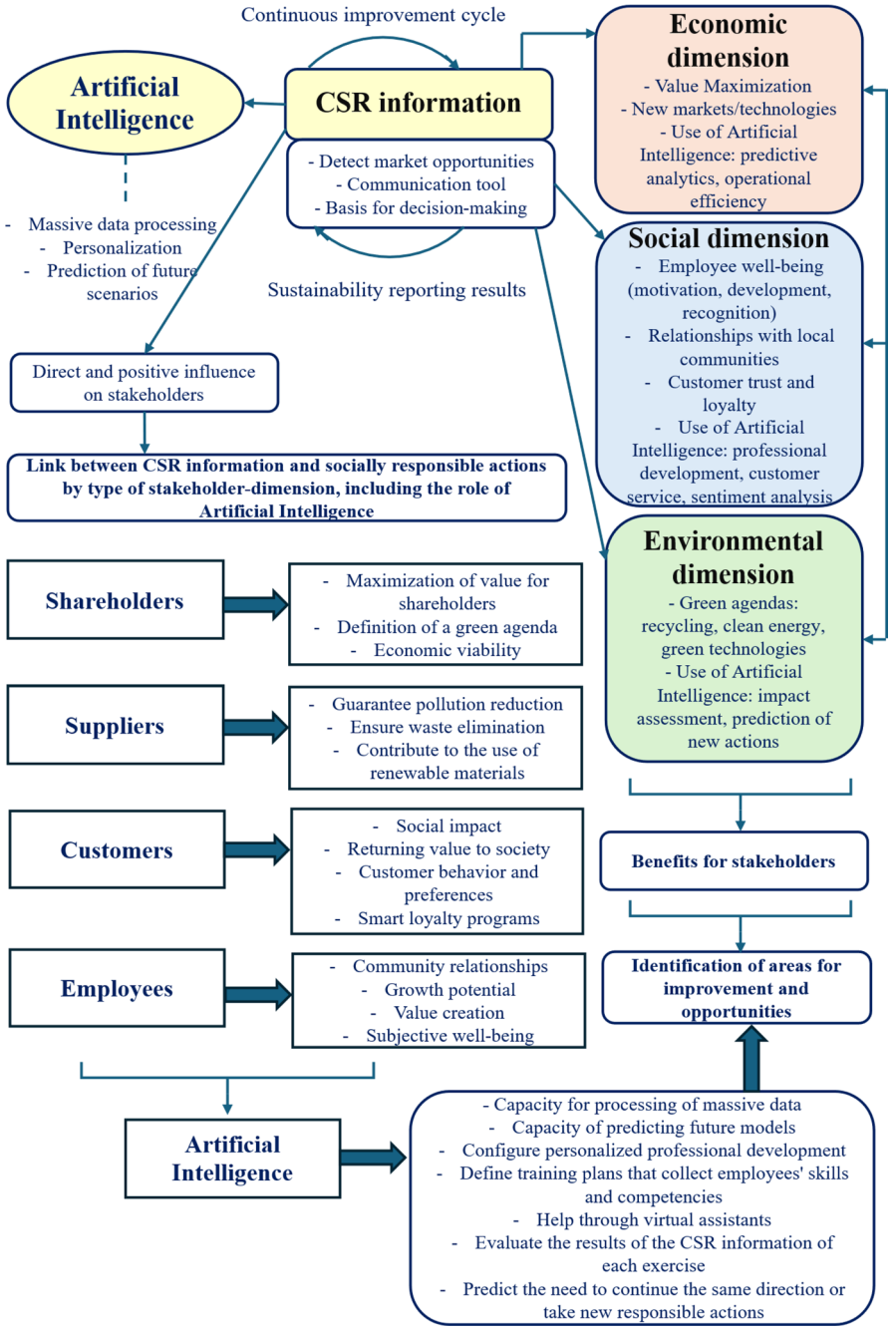


Fig. 1 Corporate social responsibility (CSR) information and implementation of social responsibility actions Source: Authors

in the present research, with low priced virgin materials and high upfront investment costs highlighted as key concerns. Overcoming these obstacles is essential to accelerate the adoption of circular practices (Kirchherr et al. 2018; Ranta et al. 2018; García-Quevedo et al. 2020).

Regulatory barriers in the CE pose challenges because of, for example, few supportive policy frameworks and many obstructive laws and regulations, including restrictions on transporting waste materials across borders and regulations that prevent the use of recycled materials in certain products. Legal barriers have not been identified in the literature as primary concerns, but governmental intervention can remove the obstacles raised by regulatory factors (Kirchherr et al. 2018; Ranta et al. 2018; Gedam et al. 2021).

Financial barriers also pose significant challenges to the widespread adoption of CE principles. High initial investment costs are especially problematic in CE support infrastructure such as reverse logistics, research and development, and the certification of new CE models (Hart et al. 2019). In addition, uncertainty surrounds the future value of materials, particularly in construction with low priced new materials and even lower end-of-life values. Weak business success in and few compelling case studies of the CE further hinder adoption, and alignment is often lacking between business and environmental cases. Limited access to financing and financial resources frequently presents barriers that impede the implementation of CE practices (Ranta et al. 2018; Hina et al. 2022).

Technological barriers to CE transitions may include challenges in the development and application of suitable equipment for recycling, remanufacturing, and circular design processes. These obstacles can hinder the effective implementation of circular strategies in industries and limit the widespread adoption of circular business models (Kirchherr et al. 2018; Gedam et al. 2021). Some technological barriers comprise limitations on the efficiency or scalability of recycling technologies, complications in achieving high-quality remanufactured products, and challenges in integrating circular design principles into product development (Bianchini et al. 2019; Arena et al. 2021). Related hurdles include, among others, insufficient investment in circular technology research and development, the absence of standardized procedures, and inadequate infrastructure for collecting and processing recyclable materials (Jaeger and Upadhyay 2020; Grafström and Aasma 2021).

AI can be integrated into CE resource management and transitions to address the above challenges. For instance, AI optimizes recycling and material recovery processes by enhancing waste sorting and separation, thereby increasing the efficiency of the circular value chain. In addition, AI is able to analyze large volumes of data related to resource consumption and market trends, which then inform investment decisions about circular technology research and development. This strategy can reverse the tendency to invest insufficiently in CE technologies. Implementing AI-based systems may also help standardize processes and improve the management of infrastructure for collecting and processing recyclable materials, thus overcoming the hurdles of inadequate standardization and technical support.

More researchers are seeking to identify the incentives that encourage traditional businesses to adopt CE strategies (Asgari and Asgari 2021). The literature mentions a wide range of inducements to adopt CE and sustainable practices in the construction

industry (Hart et al. 2019; Hina et al. 2022; Neves and Marques 2022). These incentives range from establishing standards and certifications that promote the reuse of structural materials and the usage of recycled materials to creating reverse logistics infrastructure such as material markets and storage facilities and addressing practical challenges to the reuse of materials released by building renovation or demolition (Hart et al. 2019).

Innovation and technological development also play a crucial role in the CE because they unlock new opportunities. Companies need to explore using technologies such as three-dimensional printers, sensors and controls, the Internet of things, and exchange platforms for underutilized assets (Ranta et al. 2018). Collaboration among different supply chain actors is another key element, as well as advanced design tools (e.g., building information models, material databases, passports, and assessment methods for reusing built structures) (Neves and Marques 2022).

Finally, circular business models should be developed that encourage companies to recycle materials and optimize resources in construction, which is a crucial driver of CE transitions (Govindan and Hasanagic 2018). Recent studies have sought to optimize recycling processes and inform investment decisions, stressing that AI can actively facilitate the implementation of circular business models by supporting product-as-a-service strategies, predictive maintenance, and reverse logistics (Ellen MacArthur Foundation 2019; Madanaguli et al. 2024). For instance, AI-powered systems are able to monitor product usage data to extend product lifecycles, predict component failure to facilitate remanufacturing, and manage resource flows across supply chains to close material loops. These capabilities position AI as both an analytical tool and strategic enabler of new business models aligned with CE principles, which accelerate the transition from linear to circular value creation.

The second hypothesis defined for the current research addressed RQ3, defining BICE based on the implementation of CSRAs. Based on the above findings, this hypothesis was written as follows:

Hypothesis 2 (H2) *The implementation of CSRAs will facilitate the identification of BICE.*

2.4 BICE

The barriers to the CE thus need to be identified and overcome and the right initiatives implemented in order to expand the CE. Cultural barriers should be removed, such as a lack of consumer interest and awareness and resistance within company culture, to speed the shift toward more sustainable practices in both consumer behavior and business operations (Kirchherr et al. 2018; Guerra and Leite 2021). Similarly, market barriers have to be tackled (e.g., low priced virgin materials and high upfront investment costs) to enable businesses to invest in circular initiatives and develop competitive circular products. Regulatory barriers comprise obstructive laws and regulations, which can be reduced through supportive policy frameworks that facilitate the implementation of circular practices across borders (Farooque et al. 2019; Mehmood et al. 2021).

In addition, financial barriers include steep initial investment costs and limited access to financing, so governments need to remove these challenges by establishing funding mechanisms and strengthening financial support for circular initiatives. Technological obstacles arise, for instance, to recycling technologies and circular design processes, which can be overcome by increasing research and development and stakeholder collaboration to increase innovation and the adoption of suitable technologies (Mähönen 2018; Delouyi et al. 2023). Overcoming these barriers and implementing incentives can significantly contribute to the promotion and adoption of CE principles leading to resource optimization, waste reduction, and environmental sustainability in diverse industries (Bressanelli et al. 2022; Aithal and Aithal 2023; Acquier et al. 2024).

The third hypothesis proposed for the present study focused on RQ4. That is, this hypothesis sought to confirm whether pinpointing BICE fosters the increased use of CE strategies:

Hypothesis 3 (H3) *The identification of BICE will directly and positively contribute to the incorporation of CE principles.*

2.5 CSRI and CE

Organizations are currently adopting new models of CE based on the rational exploitation and regeneration of resources, conscious design of materials, and their reuse via returns to specific cycles (Ellen MacArthur Foundation 2015; Stewart and Niero 2018; Suárez-Eiroa et al. 2019; Barreiro-Gen and Lozano 2020; Bassi and Dias 2020; Marco-Fondevila et al. 2021). CE models concentrate on environmental protection while maintaining the maximum value of products throughout their life cycle and optimizing their usefulness in the economy (Guranathne et al. 2021). Concurrently, novel CE approaches imply the transformation of value chain processes, incorporating sustainable innovations that encourage industrial redesign while considering the importance of information systems (Kunc et al. 2020; Guranathne et al. 2021).

In CSRI, multiple indicators focus on the three key dimensions (i.e., economic, social, and environmental) and align with the principles of CE, thereby facilitating the management of circular models (Rossi et al. 2020). The current literature review corroborated Morea et al. (2021) approach to CSR—and thus to CSRI. That is, the CE can be integrated into the CSR framework despite having a different theoretical foundation, given the empirical evidence available for the attention multinational companies pay to circularity in their CSR reports. Falkenberg et al. (2023) also argue that the CE is being promoted based on CSRI in the agri-food sector, including a considerable increase since 2016 in CSR reports. However, the cited authors warn of weaknesses in the CE and the need to meet other obligations generated by EU requirements.

The literature reports that the incorporation of CE content and practices into CSRR is often superficial and inconsistent, indicating significant room for joint CSR-CE research (Opferkuch et al. 2022). Comprehensive models should be created that include all organizational activities, integrating the economic, social, and environmental impacts influenced by CE principles (Sauvé et al. 2016; Breuer et

al. 2018; Johansson and Henriksson 2020). Other research has found contradictory evidence of companies' CSR reports communicating multiple objectives typical of a circular approach (i.e., ecodesign, reuse, low energy consumption, and zero emissions) (Morea et al. 2021). More specifically, the adoption of CE practices has been gradual from an environmental point of view, starting with definitions and evaluations of environmental capabilities to determine accountability (Scarpellini et al. 2020; Llena-Macurulla et al. 2023).

Environmental management disclosure may fall short of directly expressing an orientation toward the CE, so awareness must be raised of—and the capacity and infrastructure developed to improve—the inclusion in CSRI of CE activities (Guranathne et al. 2021). Parallel conclusions were reached by Marco-Fondevila et al. (2021), who found that the largest companies in Spain (i.e., IBEX35) perceive the CE as different from the European Community's approach in the EU's Action Plan and environmental sustainability framework, without establishing a direct link with CSRI.

The present literature review confirmed that CSRI is closely related to the CE in five ways. The first connection is transparency and accountability. Companies that adopt CE principles need to be transparent about their sustainable practices, and organizational accountability involves meeting the standards of disclosure and transparency embraced by businesses (Marco-Fondevila et al. 2018). CSR entails reporting openly and honestly about sustainability actions and results—essentially a demonstration of commitment to the CE (Mani et al. 2016). The current findings indicate that transparency and accountability, along with management accounting, favor CE practices (Di Vaio et al. 2023). More specifically, Marco-Fondevila et al. (2018) ascertained that SMEs lack sufficient awareness and understanding of CSR and the CE, verifying a distrust of these different approaches when analyzing accountability standards and environmental proactivity goals. The literature thus indicates that companies' internal and geographical factors have a significant effect on accountability and CE strategies.

The second link between CSRI and the CE is resource management. CSR involves the responsible management of natural resources, and the CE focuses on reuse, recycling, and waste reduction (Scarpellini et al. 2019). CSR initiatives can accentuate possible barriers to CE practices, including difficulties in investing in the CE and finding recycled products (Scarpellini et al. 2019). Nonetheless, companies that practice CSR are more inclined to adopt CE strategies in order to minimize environmental impacts and improve resource efficiency (Geissdoerfer et al. 2017).

The third connection is sustainable innovation. CSR incentivizes companies to innovate in ways that benefit society at large and the environment, thereby supporting the development and implementation of CE practices (Adams et al. 2016). The CE likewise encourages innovation in products and processes to maximize the reuse of materials.

The fourth link between CSRI and the CE is commitment to stakeholders. CSR includes addressing the interests of relevant internal and external groups connected to the relevant organization. The CE also requires collaboration among multiple actors along the value chain to close material cycles. Communication and cooperation are essential in both approaches (Freeman and Dmytriyev 2017). A connection exists

between CSRI and the CE in that CSR is aligned with the CE principles essential for gaining stakeholder support (Deegan et al. 2002; Beck et al. 2017). Husillos and Álvarez-Gil (2008) also found evidence that CSRI, in its environmental dimension, is directly influenced by organizational stakeholders and by managerial proactivity toward the environment and thus toward the CE.

The last link is environmental and social impacts. Both CSR and the CE focus on reducing the negative effect of business activities on the environment and society at large. CSR seeks to promote sustainable and responsible practices, which are aligned with CE strategies such as designing for longevity and waste reduction (Bocken et al. 2016). More specifically, manufacturing and usage are bound together in the extraction, manufacturing, and distribution processes typical of the CE, as well as being directly associated with environmental and social performance (Palacios-Manzano et al. 2024; Di Vaio et al. 2023). CSRI provides the appropriate measures to evaluate social, environmental, and economic impacts, thereby contributing to effective circular business models (Scarpellini 2022).

In short, CSRI facilitates and supports CE transitions, demonstrating that company operations are responsible and sustainable, including any interactions with society at large and the environment (Bassi and Dias 2020). CSR reports enhance the public's understanding of CE activities, create opportunities for more initiatives, and inform stakeholders about the development of future strategies (Barnabè and Nazir 2021).

Despite the topicality and importance of these topics, experts have not yet acknowledged that CSRI and integrated reports clearly and directly lead to CE practices (Guranathne et al. 2021), which makes the current research novel and relevant. Given that the literature has yet to confirm a direct link between sustainability reporting and the CE, the current study sought to fill the gap by delving deeper into the relationship between CSRR and the CE. The final hypothesis, therefore, addressed RQ5, namely, how CSRI conditions CE practices:

Hypothesis 4 (H4) *Access to CSRI will directly and positively determine the development of CE strategies.*

The theoretical framework affirmed that CSR and the CE are interconnected concepts (i.e., RQ1). Figure 2 presents the proposed connections examined in the subsequent analyses.

3 Methods

3.1 Questionnaire, sample, and data collection

The decision was made to focus this study exclusively on social economy entities because of their growing importance and potential for generating positive social and environmental impacts. These organizations can also significantly promote sustainability through initiatives dedicated to this goal, which translate into tangible actions aligned with CSR and the CE. A broader sample could have included conventional businesses, but focusing on social economy entities provided more insights into

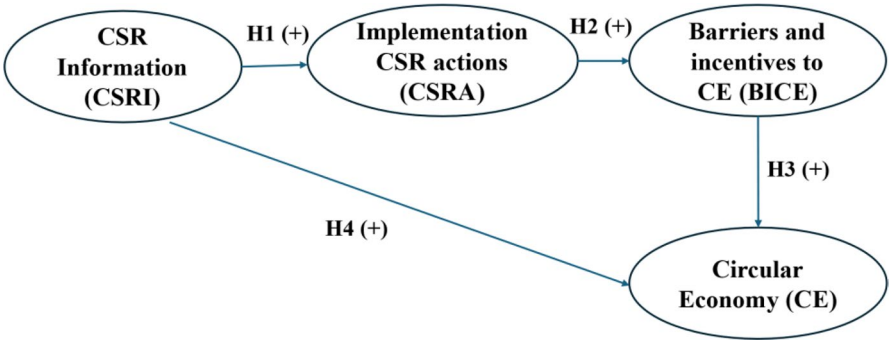


Fig. 2 Conceptual model Note. CSR = corporate social responsibility; H = hypothesis; CE = circular economy. Source: Authors

these organizations' specific dynamics, barriers, and incentives, including their combination of economic objectives with clear social missions. In addition, the research complemented previous studies conducted in Spain and other countries, which have tended to analyze the business sector in general or specific sectors without clearly differentiating the results for social economy entities.

The exclusive focus on social entities highlighted the specific characteristics of these organizations as compared to conventional businesses, such as dual social and economic objectives and unique forms of governance and management. Gallardo-Vázquez et al. (2024a, b, c) stress that social enterprises are intrinsically committed to generating social value, which directly influences their strategies and results. This key feature has sometimes been overlooked by studies that include a more heterogeneous sample of companies.

Research focused on social organizations in Spain has strengthened the literature by providing more precise, contextualized evidence on how social economy entities adopt and promote CE practices—a topic that has received limited attention. Studies have also shown that these organizations face specific barriers and opportunities when implementing CE models due to these firms social features and missions (Gallardo-Vázquez et al. 2024a, b, c). Investigations (e.g., Bacq and Janssen 2011) have underlined the uniqueness of social enterprises' dual economic and social objectives, which influence their management structures and ability to integrate sustainable innovations. However, researchers often group together different types of organizations when their studies focus on the CE in more general business contexts (e.g., Geissdoerfer et al. 2017 and Kirchherr et al. 2017), which can blur the special characteristics of social economy entities.

In Spain, recent research conducted by Gallardo-Vázquez et al. (2024a, b, c) confirmed that barriers and incentives are positively associated with the results reported and that a lack of specialized training in human resources is always a significant factor. These findings emphasize the need for differentiated methodological approaches to provide a better understanding of BICE in companies with a strong commitment to social goals. More tailored methods can deepen the knowledge about these particularities and generate contextualized evidence that complements and enriches previous related studies of other sectors and countries (Bacq and Janssen 2011). The current

research adopted a differentiated approach that provided a more global understanding of social enterprises and more focused recommendations for how to develop business policies and strategies specifically for this sector.

A survey was distributed to a group of social economy entities in Extremadura. The questionnaire comprised two main sections: organizational characteristics and action-focused items assessing each respondent's knowledge and behavior concerning CSR and the CE. The participants' perceptions were evaluated using a Likert-type scale ranging from 1 to 7 (1 = "Little knowledge"; 7 = "Very extensive knowledge"). The survey was distributed via email from November 2022 to December 2023. The final sample consisted of 129 entities, with a response rate of 37% (see Table 1).

A statistical examination of the data (see Table 2) revealed that the organizations participating in the study were predominantly cooperative societies (54.3%), followed by associations (18.6%), special employment centers (10.1%), employment companies (7.7%), foundations (4.6%), agrarian transformation firms (3.1%), and special entities (1.6%). Other categories of social economy organizations were absent from the sample (i.e., insertion companies, social security and mutual insurance firms, and rural savings banks and credit cooperatives). These organizations were considered in the study at a theoretical level, but they failed to respond to the questionnaire so their opinion was excluded. In terms of sectors, 52.7% of the enterprises were from the tertiary and service sector, with the primary sector representing 26.4% and secondary sector 20.9%. Regarding organization size, the number of employees per entity showed that the highest proportion worked for enterprises with fewer than five workers (51.9%). Those with 6–10 workers and 11–25 workers accounted for 13.2% and 14%, respectively. These segments were followed closely by organizations with 26–50 workers and 51–100 workers, comprising 7% and 7.7% each. The remaining 6.2% constituted enterprises with over 100 workers.

Before the data were processed, the research sample was checked for three possible types of biases: social desirability, nonresponse, and common method bias. To reduce social desirability bias, the survey was conducted anonymously according to Fisher's (1993) guidelines. To address nonresponse bias, the initial responses were compared with subsequent ones after dividing them into two groups: one comprising 80% of the initial responses and the other the remaining responses. An analysis of

Table 1 Technical sheet

Data on sample	
Research universe and geographical scope	Social economy enterprises operating in Extremadura, Spain
Techniques used to gather information	Structured Google questionnaire sent by email
Population	350
Sample	129
Response collection period	November 2022 to December 2023
Participation rate	37%
Sample error	6.87%
Confidence level	95%

Source: Authors

Table 2 Participant profile

Sample information	Number	%
Categories of social economy entities that completed questionnaire		
Cooperative society	70	54.3%
Association	24	18.6%
Special employment centers	13	10.1%
Employment society	10	7.7%
Foundations	6	4.6%
Agrarian transformation firms	4	3.1%
Special entities	2	1.6%
Industry classification of entities		
Primary sector	34	26.4%
Secondary sector	27	20.9%
Tertiary sector	68	52.7%
Size of entities in terms of workforce (w)		
$w<5$	67	51.9%
$6<w<10$	17	13.2%
$11<w<25$	18	14%
$26<w<50$	9	7%
$51<w<100$	10	7.7%
$w>100$	8	6.2%

Source: Authors

variance showed no significant differences between these groups, thereby ruling out nonresponse bias. Finally, to evaluate common method bias, Harman's single-factor test (Podsakoff et al. 2003) was run. The results indicate that five factors, with a Kaiser–Meyer–Olkin measure of sampling adequacy of 0.921 and a significant Bartlett's test of sphericity value ($p=0.000$), accounted for 58.8% of the total variance in the model. The main factor explained only 39.41% of the variance, suggesting that common method variance bias was insignificant.

3.2 Measurement scales

The survey sought to analyze four relationships between the constructs or latent variables: CSRI, implementation of CSRAs, BICE, and CE. The four constructs are lower order composites (LOCs) capable of measuring multidimensional concepts drawn from the literature (Henseler 2017a). The variables were classified as reflective constructs and estimated in mode A.

The measurement indicators for each construct were based on work done by Scarpellini et al. (2019); Aranda-Usón et al. (2020); Scarpellini (2022); and Gallardo-Vázquez et al. (2024a, b, c). The focus of each construct was defined as follows. First, CSRI was evaluated using 7 indicators of the level of CSRI knowledge, integration of CSRI into corporate strategy, availability of personnel to manage CSRI, competitive advantages obtained for the entity, and highest performance obtained. Second, the implementation of CSRAs was assessed with 11 indicators of, among others, the dissemination of CSR plans; economic, social, and environmental projects; and the establishment of alliances. Third, BICE was measured using 3 indicators of the lack of training of specialized personnel, subsidies for change implementation, and citizen awareness campaigns and their distribution. Last, CE orientation was assessed with

7 indicators of environmental training, product and/or service redesign for enhanced functionality, provision of CE training to employees, filling of new CE professional roles, and greater collaboration among workers in the exchange of goods and services (see Appendix 1).

3.3 Analytical approach

PLS-SEM is used primarily for explanatory purposes because it facilitates theory testing and causal interpretation, whereas ANNs are used exclusively as complementary predictive tools to assess forecasting accuracy and robustness, without implying causal links. As mentioned previously, the first objective of this study was to assess organizations' orientation toward the CE via their CSRI by combining an explanatory approach (i.e., to define the underlying relationships among variables) with a predictive model of CE practices based on CSRI. The two methods were selected to assess the model's ability to anticipate CE orientation through PLS-SEM supported by AI. PLS-SEM is a statistical modeling technique used in multivariate analysis to examine relationships between latent and observed variables inferred from indicators (Chin 1998a). This method can also be part of a broader data analytical process relying on AI techniques, that is, statistical and mathematical algorithms used to estimate model parameters and test hypotheses.

SmartPLS 4 software was used to process the data (Ringle et al. 2022). This program incorporates functions that support optimization, validation, and predictive analyses—some of which can be enhanced by AI-driven tools—but the software stops short of autonomously constructing models. Users must define the theoretical framework, specify the structural relationships, and select the indicators. Thus, well-informed judgment remains essential to this model-building process to ensure conceptual coherence and theoretical validity. In line with this reasoning, Mai et al. (2021) emphasize the need to adopt tailored-fit model evaluation strategies in structural equation modeling, as the choice of evaluation criteria should depend on the specific purpose, structure, and decision context of the model.

Computer systems can be combined with human intelligence by gathering data and generating patterns for decision making based on PLS-SEM results, namely, using a combination of PLS-SEM and AI tools. The former method is especially suitable for exploratory research because PLS-SEM requires no data normality and can use small sample sizes (Hair et al. 2014). Finally, PLS-SEM tests hypotheses developed out of the available theoretical knowledge (Chin 1998b).

In addition, Python 3.11.7 software was employed to develop the ANNs for this study, together with scikit-learn library version 1.2.2. The multilayer perceptron (MLP) regressor function created and trained the neural network models to facilitate the use of MLP architecture in regression tasks. In addition, the scikit-learn train_test_split function divided the dataset into training and testing subsets to validate the performance and generalization ability of the models. This procedure was achieved with a test size of 20% and a fixed random seed to ensure consistent partitioning across runs. Separate train-test splits were done for each output variable to maintain the same input features while independently splitting the corresponding target values. This technique ensured that the neural networks were trained on a representative sub-

set of the data and then evaluated on unseen samples, which provided an empirically robust assessment of the models.

4 Results

The results were generated in five stages. Analyses were carried out, first, of the measurement model to check the reliability and validity of the items in the measurement model, second, of the structural model to assess the statistical significance of its relationships, and, third, of the model's goodness of fit. Next, the predictive power of the model was evaluated, and, finally, an importance-performance map was constructed.

4.1 Inner model

As mentioned previously, PLS-SEM was selected because of its ability to generate theory-driven models with predictive objectives, its empirically robust results when working with relatively small samples, and its capacity for handling complex relationships among latent constructs without requiring multivariate normality. These characteristics made PLS-SEM especially appropriate for analyzing CSR-CE relationships in the social economy. This method can first be used to confirm if the statistical values support the theoretical relationships proposed in the framework, which is important from an explanatory perspective. The individual reliability of each item is then evaluated to ascertain whether the shared variance between each item and its constructs is greater than the error variance (e.g., Chin and Dibbern 2010; Hair et al. 2014).

The standardized factor loadings (λ) need to be greater than 0.707 (e.g., Roberts et al. 2006; Chin and Dibbern 2010). Those items with a λ below 0.707 have to be eliminated. This step was necessary is the case of the CSRA construct, in which 4 of the initial 11 items had to be eliminated. All the remaining items in the model have loading values ranging from 0.741 to 0.933 (see Table 3), which exceed the recommended minimum value. The individual reliability of the inner model was thus confirmed. In addition, the constructs were represented as Composite LOC Mode A, so the indicators defining them had to exhibit significant correlation weights (Rigdon 2016; Henseler 2017a, b).

Next, the internal consistency was assessed based on the reliability of the latent variables, which was checked by estimating the Cronbach's alphas (CAs) and the factors' composite reliability (CR) (Nunnally and Bernstein 1994). The results should indicate how effectively the items measure the relevant latent variable. Nunnally (1978) and Vandenberg and Lance (2000) recommend scores above 0.70 or 0.80 for advanced research. The present CA values range from 0.825 to 0.958, which are satisfactory (Hair et al. 2006). These figures confirm that the scales are highly reliable (see Table 3 above). In addition, the CR analysis (i.e., rho_a and rho_c values) yielded acceptable results ranging from 0.895 to 0.965, confirming the internal consistency of the constructs.

Both the convergent and discriminant validity of the constructs were also examined to evaluate the validity of the model. Convergent validity was assessed by com-

Table 3 Inner model results

Composite LOC Mode A and indicators	Indicator	Loadings (λ)	Weights	Cron-bach's alpha	Com-posite relia-bility (rho_a)	Com-posite reliability (rho_c)	Average variance ex-tracted
CSRI (CSRI)	CSRI1	0.867	.150	.950	.956	.959	.772
	CSRI2	0.932	.172				
	CSRI3	0.741	.130				
	CSRI4	0.908	.163				
	CSRI5	0.924	.178				
	CSRI6	0.924	.180				
	CSRI7	0.839	.159				
Implement-ation of CSR actions (CSRA)	CSRA4	0.753	.174	.911	.913	.929	.653
	CSRA5	0.807	.169				
	CSRA6	0.801	.177				
	CSRA8	0.864	.197				
	CSRA9	0.785	.177				
	CSRA10	0.812	.162				
	CSRA11	0.832	.180				
Barriers and incen-tives to circular economy (BICE)	BICE1	0.846	.389	.825	.841	.895	.741
	BICE2	0.829	.332				
	BICE3	0.905	.437				
Circular economy (CE)	CE1	0.841	.145	.958	.959	.965	.798
	CE2	0.910	.171				
	CE3	0.908	.152				
	CE4	0.877	.166				
	CE5	0.873	.168				
	CE6	0.933	.164				
	CE7	0.908	.152				

Note. LOC = lower order composite; CSR = corporate social responsibility; CSRI = CSR information; significance and standard deviations determined by performing 10,000 bootstrap repetitions

Source: Authors

puting the average variance extracted (AVE) (Fornell and Larcker 1981; Hair et al. 2011), which indicates the extent to which the different measures for a construct yield similar results. The AVE values range from 0.653 to 0.798, so all surpass the required threshold of 0.500. The model constructs thus have satisfactory convergent validity as they meet the recommended minimum criterion (Hair et al. 2010) (see Table 3 above), and the internal consistency of the latent variables was confirmed.

Discriminant validity was then checked for possible differences between each construct and its items with respect to other constructs. The analyses included Fornell and Larcker's (1981) criterion and the square root each variable. These values appear on the diagonal and in bold in Table 4. The numbers must be greater than the inter-construct correlations of the model (Roldán and Sánchez-Franco 2012; Henseler et al. 2015). The results are satisfactory since the Fornell and Larcker's criterion confirms the discriminant validity of the model. Discriminant validity was also evaluated using the heterotrait-monotrait ratio (see Table 4). Roldán and Sánchez-Franco (2012) and Henseler et al. (2015) suggest that a maximum threshold of 0.90 is acceptable. The values presented in Table 4 remain below this maximum threshold. These findings verify that all constructs incorporated into the model fulfill the predefined

Table 4 Construct discriminant validity (Fornell and Larcker's and heterotrait-monotrait ratio criteria)

Construct	CSRI	CSRA	BICE	CE	Construct	CSRI	CSRA	BICE	CE
CSRI	0.879				CSRI				
CSRA	0.841	0.858			CSRA	0.898			
BICE	0.662	0.761	0.861		BICE	0.741	0.869		
CE	0.819	0.785	0.694	0.893	CE	0.854	0.837	0.772	

Note. CSRI = corporate social responsibility information; CSRA = corporate social responsibility actions; BICE = barriers and incentives to circular economy; CE = circular economy

Source: Authors

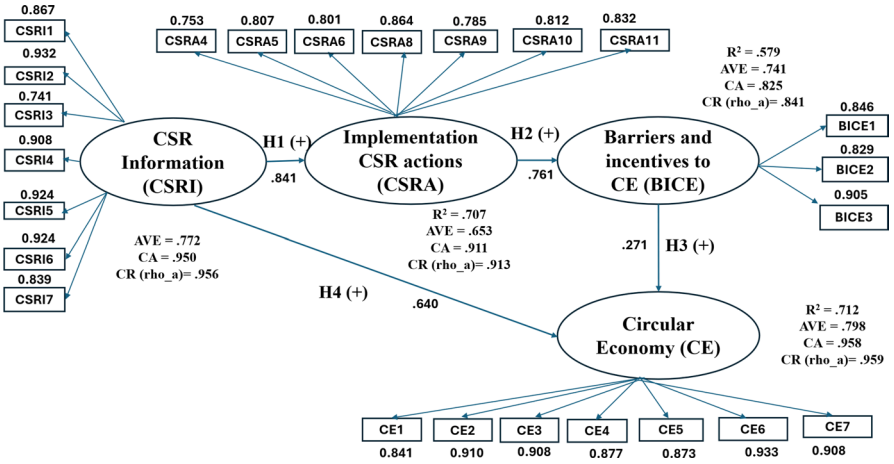


Fig. 3 Evaluation of measurement model Note. CSR = corporate social responsibility; R^2 = coefficient of determination; AVE = average variance extracted; CA = Cronbach's alpha; CR = composite reliability; H = hypothesis. Source: Authors

criteria for discriminant validity. Figure 3 presents the results of the evaluation of the measurement model.

4.2 Outer model

In the next phase, the model was further validated by examining its applicability to independent datasets, using cross-validation techniques. Analyses were carried out of the direction, magnitude, and significance of the structural path coefficients (i.e., β) to assess the structural model (Wright et al. 2012). If the β values are significant, the hypotheses have received sufficient support. These weights should ideally surpass 0.2 but preferably exceed 0.3 (Chin 1998a).

A nonparametric resampling technique was applied, more specifically, a bootstrapping procedure with 10,000 subsamples utilizing a Student's t-distribution based on a tail with $n - 1$ degrees of freedom, in which n represents the number of subsamples (Chin 1998a; Hair et al. 2011). This procedure provided both the standard errors and values of the Student's t-statistic for the parameters. The analysis performed with the sample data yielded satisfactory results because the β values reach the recommended

threshold (Chin 1998b). The four hypotheses corresponding to the model were confirmed. The variables have significant positive effects with β values of 0.841*** ($p<0.001$), 0.761*** ($p<0.001$), 0.271* ($p<0.05$), and 0.640*** ($p<0.001$), respectively, and different levels of significance (see Table 5).

These results provide empirically robust support for the idea that having access to CSRI is directly and positively associated with the implementation of CSRAs (i.e., H1). The analyses also confirmed that the implementation of CSRAs facilitates the identification of BICE (i.e., H2). In addition, statistical support was found for the assertion that identifying BICE contributes directly and positively to the incorporation of CE strategies (i.e., H3), although this link is less statistically significant. Finally, the results confirm that access to CSRI is directly and positively associated with the development of CE practices (i.e., H4). For all four hypotheses, the variables have significant positive effects with *p*-values of less than 0.05 and 0.001 (see Table 5 above), so the reliability of the model was verified. The bootstrapping procedure further ascertained acceptable percentile confidence intervals (CIs), and any bias was minimized. For the hypotheses, the CI values exceed zero, as recommended by Chin (1998a) (see Table 5 above).

Next, the effect size (f^2) was estimated to gauge how much the exogenous constructs contribute to explaining the endogenous constructs (Cohen 1988). Following Cohen's (1988) guidelines, the f^2 values were interpreted as small (0.02), medium (0.15), or large (0.35) to indicate the relative contribution of each exogenous construct to the explained variance of the relevant endogenous variable and to allow more substantive interpretation going beyond statistical significance. The results indicate a large effect for H1 (i.e., CSRI –>CSRA) ($f^2=2.408$) and H2 (i.e., CSRA –>BICE) ($f^2=1.375$) and a moderate effect for H3 (i.e., BICE –>CE) ($f^2=0.143$) and for H4 i.e., CSRI –>CE) ($f^2=0.799$) (Cohen 1988) (see Table 5 above).

The model's explanatory power (i.e., in-sample prediction) was also analyzed for all endogenous constructs to assess the strength of each structural path (Chin 2010). The coefficient of determination (R^2) values (i.e., explained variance) for the latent dependent variables should be greater than or equal to 0.1 (Falk and Miller 1992; Chin 2010; Hair et al. 2019). In the present study, the R^2 values are satisfactory ($R^2_{CSRA}=0.707$, $R^2_{BICE}=0.579$, $R^2_{CE}=0.712$), so they meet this criterion and confirm the model's explanatory capacity.

Various goodness-of-fit indices were examined to assess the model's fit (Henseler et al. 2016; Henseler 2017a, 2017b; Benitez et al. 2020; Henseler and Schuberth 2020). The first to be estimated was the standardized root mean square residual (SRMR) index and the normed fit index (NFI). These indices should respect specific thresholds (SRMR<0.08, NFI>0.90). In the current research, the SRMR score is 0.069, below the upper limit, and the NFI score is 0.856 (i.e., quite close to the top value) (Hu and Bentler 1998), so both scores indicate an acceptable goodness-of-fit.

The second set of indices were two overall model fit measures based on bootstrap statistical inference: the unweighted least squares discrepancy and geodesic discrepancy. The 99% CIs derived from the sampling distributions provide the original values of these statistics, both in the estimated and saturated models. More specifically, for the 99th percentile (HI 99) based on bootstrapping, the values of the discrepancy measures fall below this threshold, which suggests that the model has a good fit.

Table 5 Hypotheses contrasted (correlation and variance explained) and effects on endogenous variables

Hypo-thesis (H)	Path coeffi-cient (β)	VIF	f^2	p-value	Stan-dard error	Corre-lation	*t*-value (boot-strap)	Percentile 95% confidence interval	Sup-por-ted (Yes/No)
H1: CSRI → CSRA (R^2_{CSRA} = .707)	.841 ***	1.000	2.408	.000	0.026	.841	32.751	[.786; .888] Sig	Yes
H2: CSRA → BICE (R^2_{BICE} = .579)	.761 ***	1.000	1.375	.000	0.043	.761	17.739	[.671; .839] Sig	Yes
H3: BICE → CE (R^2_{CE} = .712)	.271 *	1.779	0.143	.003	0.090	.694	2.997	[.103; .455] Sig	Yes
H4: CSRI → CE (R^2_{CE} = .712)	.640 ***	1.779	0.799	.000	0.080	.819	7.975	[.470; .781] Sig	Yes

Note. VIF = variance inflation factor; CSRI = corporate social responsibility information; CSRA = corporate social responsibility actions; R^2 = coefficient of determination; Sig. = significant effect; BICE = barriers and incentives to circular economy; CE = circular economy; bootstrapping based on 10,000 subsamples, applying a one-tailed test for a Student's t-distribution; * $p < .05$; ** $p < .01$; *** $p < .001$; based on a Student's $t_{(4999)}$ one-tailed distribution; $t_{(0,05,\ 4999)} = 1.645$; $t_{(0,01,\ 4999)} = 2.327$; $t_{(0,001,\ 4999)} = 3.092$

Source: Authors

4.3 Model predictive power

A predictive perspective shifts the focus to the model's ability to forecast outcomes accurately, which is assessed using the root mean square error (RMSE) and mean absolute error (MAE). PLS-SEM prioritizes increasing this predictive capacity, and this method is often preferred when the primary objective is to predict dependent variables rather than provide explanations. This strength is a significant advantage of PLS-SEM as it produces models that can accurately generate predictions (Shmueli and Koppius 2011).

The predictive ability (i.e., out-of-sample prediction) was assessed by conducting cross-validation with holdout samples (Evermann and Tate 2016). This step was achieved using the PLS-predict algorithm procedure (Shmueli et al. 2016) of SmartPLS version 4 software (Ringle et al. 2022). This algorithm generates *k*-fold cross-validated prediction errors and summary statistics to evaluate the model's predictive performance for both indicators and constructs.

The predictive relevance (Q^2) criterion (i.e., cross-validated redundancy) measures predictive power by assessing the significance of the dependent constructs' predictions. The model demonstrates good predictive capability if Q^2 is greater than 0 (Shmueli et al. 2016), with predictions being more accurate the closer they get to 1. The present analysis focused primarily on the key dependent constructs (i.e., CSRA, BICE, and CE), revealing that all Q^2_{predict} are greater than 0 (see Tables 6 and 7). Next, the symmetric distribution of prediction errors was analyzed. When the skewness of the indicators' absolute values is less than 1, the RMSE is used. In cases in

Table 6 Predictive power

Dependent constructs	Indicator	R^2 (explained variance)	Q^2_{predict} constructs	Q^2_{predict}	Skewness	Election
Implementation CSR actions (CSRA)	CSRA4	.707	0.702	0.558	0.140	MAE
	CSRA5			0.500	0.417	MAE
	CSRA6			0.304	0.066	MAE
	CSRA8			0.427	0.132	MAE
	CSRA9			0.484	0.446	MAE
	CSRA10			0.431	0.086	MAE
	CSRA11			0.459	0.353	MAE
Barriers and incentives to circular economy (BICE)	BICE1	.579	0.430	0.267	–0.234	RMSE
	BICE2			0.260	–0.026	RMSE
	BICE3			0.413	–0.009	RMSE
Circular economy (CE)	CE1	.712	0.663	0.593	0.634	MAE
	CE2			0.603	0.233	MAE
	CE3			0.547	0.666	MAE
	CE4			0.420	0.313	MAE
	CE5			0.412	0.184	MAE
	CE6			0.486	0.790	MAE
	CE7			0.600	0.113	MAE

Note: R^2 = coefficient of determination; Q^2 = predictive value; MAE = mean absolute error; RMSE = root mean square error

Source: Authors

Table 7 Predictive power

Indica-tor	PLS-SEM RMSE	PLS-SEM MAE	$Q^2_{predict}$	Indica-tor	LM-RMSE	LM-MAE	Indicator	PLS-LM RMSE	PLS-LM MAE
CSRA4	1.389	1.142	0.558	CSRA4	1.359	1.062	CSRA4	0.030	0.080
CSRA5	1.490	1.203	0.500	CSRA5	1.476	1.168	CSRA5	0.014	0.035
CSRA6	1.601	1.221	0.304	CSRA6	1.601	1.198	CSRA6	0.000	0.023
CSRA8	1.427	1.110	0.427	CSRA8	1.378	1.053	CSRA8	0.049	0.057
CSRA9	1.459	1.177	0.484	CSRA9	1.510	1.197	CSRA9	–0.051	-0.020
CSRA10	1.506	1.191	0.431	CSRA10	1.505	1.154	CSRA10	0.001	0.037
CSRA11	1.577	1.220	0.459	CSRA11	1.619	1.271	CSRA11	–0.042	-0.051
BICE1	1.669	1.302	0.267	BICE1	1.730	1.301	BICE1	–0.061	0.001
BICE2	1.684	1.378	0.260	BICE2	1.710	1.372	BICE2	–0.026	0.006
BICE3	1.543	1.245	0.413	BICE3	1.624	1.265	BICE3	–0.081	-0.020
CE1	1.226	0.939	0.593	CE1	1.210	0.873	CE1	0.016	0.066
CE2	1.263	0.996	0.603	CE2	1.304	0.956	CE2	–0.041	0.04
CE3	1.390	1.045	0.547	CE3	1.395	1.008	CE3	–0.005	0.037
CE4	1.584	1.191	0.420	CE4	1.604	1.234	CE4	–0.020	-0.043
CE5	1.482	1.151	0.412	CE5	1.422	1.064	CE5	0.060	0.087
CE6	1.439	1.091	0.486	CE6	1.458	1.126	CE6	–0.019	-0.035
CE7	1.338	1.037	0.600	CE7	1.383	1.009	CE7	–0.045	0.028

Note. PLS-SEM=partial least squares-structural equation modeling; RMSE=root mean square error; MAE=mean absolute error; Q^2=predictive value; LM=linear modeling; CSRI=corporate social responsibility information; CSRA=corporate social responsibility actions; BICE=barriers and incentives to circular economy; CE=circular economy

Source: Authors

which the skewness of the absolute values is greater than 1, the MAE is used (see Tables 6 and 7).

The proposed model has predictive power for the three constructs, with a positive $Q^2_{predict}$. For CSRA and CE, the model required MAE and, for BICE, RMSE was needed. In relation to the CSRA construct, an analysis of the indicators revealed that CSRA9 and CSRA11 have the recommended negative differences for RMSE and MAE. Similarly, the BICE, BICE1, and BICE2 indicators have negative differences for RMSE, again as suggested, and positive differences for MAE. BICE3 also has negative differences for RMSE, as recommended, and for MAE. Regarding CE, CE2, CE3 and CE7, negative differences appear for RMSE and positive differences for MAE, as suggested. In addition, CE4 and CE6 present the recommended negative differences for both RMSE and MAE. Therefore, the model was shown to have good predictive capacity, which confirms that AI can contribute to the definition of predictive models, which satisfies RQ6.

4.4 IPMA

The PLS-SEM analysis provided insights into how well the selected constructs explain other variables in the structural model. IPMA was also conducted to extend these findings. This valuable tool in conjunction with PLS-SEM compares each construct's performance in relation to the others. IPMA seeks to pinpoint which precursor constructs are extremely important but poor performers, thereby identifying areas needing improvement and specific interventions (Ringle and Sarstedt 2016).

Table 8 Importance-performance map analysis results for antecedents of circular economy (CE)

Antecedents of circular economy (CE)	CE	
	Total effect (importance)	Index value (performance)
CSR information (CSRI)	0.813	46.525
Implementation CSR actions (CSRA)	0.206	60.930
Barriers and incentives to CE (BICE)	0.271	59.754
Mean	0.43	55.736

Note. CSR = corporate social responsibility

Source: Authors

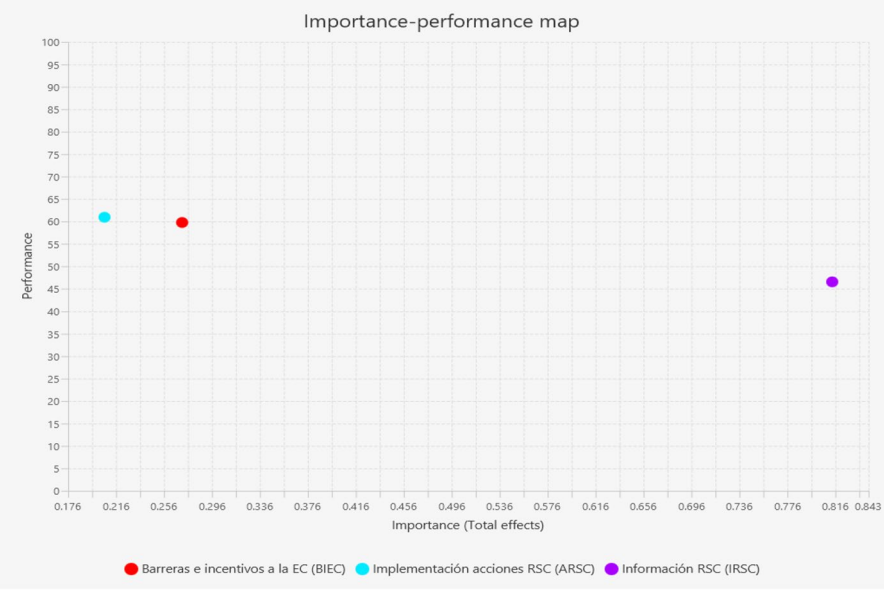


Fig. 4 Importance-performance map Source: Authors

The resulting four-quadrant diagram presents the variables on vertical and horizontal axes (Martilla and James 1977; Hair et al. 2019) based on their values ranging from lowest to highest, which provides a clear explanation of the relationships between the constructs. The first axis represents the variables' performance, and the horizontal one signifies the perceived importance of these constructs. The results comprise the importance-performance map of each exogenous variable and its impact on endogenous variables (i.e., performance) (see Table 8 and Fig. 4).

Based on the findings shown in Table 8 and Fig. 4 above, the importance of CSRI is almost double the average value, while its performance is below average. This area's performance needs to be improved significantly, but its importance can be maintained or increased. In contrast, CSRA and BICE exhibit a well below average importance, while their performance is somewhat above average. In this case, both constructs should be strengthened to shift to a different quadrant. Using the IPMA

results, improvements should be made to help the relevant organizations develop better and obtain more significant results with CSR and CE strategies.

4.5 Comparison of PLS-SEM and neural network results

Comparing PLS-SEM and ANN findings has become an increasingly common procedure in quantitative research, especially when contrasting a model's explanatory versus predictive capability. These methods have conceptual differences, but their combined and comparative use is considered valid and often beneficial. PLS-SEM and ANNs can thus be used to analyze complex relationships among variables even though these methods differ conceptually in their objectives and underlying logic.

PLS-SEM is a theory-driven, variance-based causal technique designed to explain the relationships among constructs through linear equations and statistically testable hypotheses. This method primarily concentrates on estimating the strength and significance of links to provide a clearer interpretation and theoretical validation of the proposed model. In contrast, ANNs comprise a data-driven, non-linear predictive approach inspired by the structures and functions of the human brain. These networks are unable to confirm causal hypotheses but instead maximize predictive accuracy by capturing non-linear and interaction effects that traditional models may overlook. Thus, PLS-SEM contributes to the explanatory understanding and theoretical validation of causal mechanisms while ANNs complement the former method by enhancing models' predictive power and uncovering hidden patterns in the data (see Table 9).

The present comparative evaluation relied on the assessment criteria shown in Table 10. The ANN analysis was conducted after the PLS-SEM, and both the measurement and structural models were evaluated. This process validated the predictive capability of the PLS-SEM model using the latent variable scores as input neurons. Two ANN procedures (i.e., ANN1 and ANN2) were carried out to depict the relationships among the latent constructs measured in this study.

ANN1 was a multi-output neural network that used only the CSRI construct as a predictor to measure CSRA, BICE, and CE simultaneously. This network had a two-hidden-layer architecture with 64 and 32 units, respectively. ANN1 captured the overall influence of CSRI on the three dependent constructs within a single model, whose performance was evaluated using fit metrics such as the R^2, Q^2, and prediction errors.

Table 9 Conceptual differences between partial least squares structural equation modeling (PLS-SEM) and artificial neural networks (ANNs)

Aspect	PLS-SEM	ANNs
Type of model	Based on structural equations and theoretical causal relationships	Based on machine learning (i.e., non-linear prediction)
Main assumption	Linear relationships among latent constructs	Complex, non-linear relationships
Objectives	Causal explanation and hypothesis validation	Prediction and optimization
Key outputs	Path coefficients, R^2, Q^2, and significance levels	Prediction errors, R^2, RMSE, MAE, and variable importance

Note. R^2 = coefficient of determination; Q^2 = predictive value; RMSE = root mean square error; MAE = mean absolute error

Source: Authors

Table 10 Comparative evaluation of partial least squares structural equation modeling (PLS-SEM) and artificial neural networks (ANNs)

Evaluation criterion	Compared features	Interpretation
Coefficient of determination (R^2) in both models	Amount of variance explained	The higher the value, the greater the explanatory power
Predictive relevance (Q^2) of PLS-SEM vs. root mean square error (RMSE) for ANNs	Out-of-sample prediction	$Q^2 > 0$ and a low RMSE as indications of good predictive performance
Variable importance	Path coefficients (i.e., PLS-SEM) vs. weights/importance (i.e., ANNs)	Assessment of whether the most influential predictors coincide
Linearity vs. non-linearity	If the ANN significantly improves R^2/accuracy, non-linear relationships exist that PLS does not capture	Not applicable

Source: Authors

The second ANN2 network was given a cascading neural network design that explicitly reflected the hierarchical structure observed among the constructs. In the first stage, CSRI predicted CSRA and CE through networks with two hidden layers of 64 and 32 units, respectively. CSRA then served as a predictor of BICE in a network with two hidden layers of 32 and 16 units each. Finally, BICE was combined with CSRI to predict the final CE construct through another network with two hidden layers of 32 and 16 units, respectively. This cascading architecture enabled the modeling of sequential dependencies and mediated relationships among the constructs and thus facilitated the interpretation of paths of influence and the computation of each predictor's normalized importance at the various stages of the network.

Positive Q^2 values confirmed the predictive power of the PLS-SEM model. The ANN models also reinforced this finding by showing a consistent predictive performance and somewhat stable cross-validated accuracy. The comparative results indicate extremely similar predictive outcomes for both methods. The models appear to capture the same underlying information and generate analogous predictions for the dataset. The neural networks, therefore, covered no additional relationships beyond those already captured by the PLS-SEM model (see Table 11).

The complementary use of PLS-SEM and ANNs enabled a more comprehensive evaluation of the proposed model. PLS-SEM validated the hypothesized linear and causal relationships between the CSR constructs and CE orientation, while the ANNs yielded similar results without showing superior predictive accuracy. No evidence was found of potential non-linear interactions that the PLS-SEM model had failed to capture. Thus, ANN analysis reinforces the empirical robustness of PLS-SEM results and can further enhance their practical applicability by identifying the most influential predictors of circular behavior.

Table 11 Comparison between partial least squares structural equation modeling (PLS-SEM) and artificial neural network (ANN) results

Criterion	PLS-SEM results	ANN_1 results	ANN_2 results	Interpretation
Coefficient of determination (R^2) for dependent constructs	R^2_{CSRA} = .707 R^2_{BICE} = .579 R^2_{CE} = .712	R^2_{CSRA} = .688 R^2_{BICE} = .429 R^2_{CE} = .656	R^2_{CSRA} = .688 R^2_{BICE} = .324 R^2_{CE} = .631	The PLS-SEM model shows strong explanatory power across constructs while the ANN models achieve comparable levels of explained variance, which provides empirically robust support for the models' stability and suggests potential nonlinear patterns in the data
Predictive relevance (Q^2)	$Q^2_{predict\ CSRA}$ = 0.702 $Q^2_{predict\ BICE}$ = 0.430 $Q^2_{predict\ CE}$ = 0.663	$Q^2_{predict\ CSRA}$ = 0.700 $Q^2_{predict\ BICE}$ = 0.430 $Q^2_{predict\ CE}$ = 0.664	$Q^2_{predict\ CSRA}$ = 0.700 $Q^2_{predict\ BICE}$ = 0.325 $Q^2_{predict\ CE}$ = 0.639	Positive Q^2 values confirm the predictive relevance of the PLS-SEM model while the ANN models reinforce this result with a consistent predictive performance and somewhat stable cross-validated accuracy
Root mean square error (RMSE)	$RMSE_{CSRA}$ = 0.551 $RMSE_{BICE}$ = 0.768 $RMSE_{CE}$ = 0.587	$RMSE_{CSRA}$ = 0.543 $RMSE_{BICE}$ = 0.810 $RMSE_{CE}$ = 0.613	$RMSE_{CSRA}$ = 0.543 $RMSE_{BICE}$ = 0.881 $RMSE_{CE}$ = 0.635	The PLS-SEM model has slightly lower RMSE values, indicating better predictive accuracy and a more stable model fit as compared to the ANN analyses

Table 11 (continued)

Criterion	PLS-SEM results	ANN_1 results	ANN_2 results	Interpretation
Mean absolute error (MAE)	$MAE_{CSRA}=0.425$ $MAE_{BICE}=0.590$ $MAE_{CE}=0.442$	$MAE_{CSRA}=0.433$ $MAE_{BICE}=0.630$ $MAE_{CE}=0.448$	$MAE_{CSRA}=0.433$ $MAE_{BICE}=0.736$ $MAE_{CE}=0.510$	The MAE results support the PLS-SEM model's robustness in terms of predictive accuracy, which indicates smaller errors and confirms the reliability of linear modeling
Path coefficients/ normalized importance of predictors	CSRI → CSRA = 0.841*** ($p<.001$) CSRA → BICE = 0.761*** ($p<.001$) BICE → CE = 0.271* ($p<.05$) CSRI → CE = 0.640*** ($p<.001$)	CSRI → CSRA = 1 CSRI → BICE = 1 CSRI → CE = 1 –	CSRI → CSRA = 1 CSRA → BICE = 1 BICE → CE = 0.239 CSRI → CE = 0.761	Both methods identify CSRI as the main predictor of CE strategies. PLS-SEM further indicates that CSRI is the main predictor of CSRA

Note. CSR = corporate social responsibility; CSRI = CSR information; BICE = barriers to and incentives for circular economy (CE) strategies; CSRA = CSR actions

Source: Authors

5 Discussion

This study adopted a dual approach that combined explanatory modeling to test theoretical relationships with predictive modeling to assess forecasting accuracy. The main contribution of the research is empirically robust evidence for the integration of CSRI and the CE in organizations' management decisions (Morea et al. 2021; Falkenberg et al. 2023). The combined use of CSRI and CE principles in companies' initiatives constitutes a significant step toward sustainability.

The present findings align with those of previous studies. That is, CE models have been characterized as focused on the rational exploitation and regeneration of resources, indicating that CE principles can be effectively integrated into CSR strategies, which enhance environmental protection while maintaining product value throughout the entire lifecycle (Bressanelli et al. 2022; Neves and Marques 2022). These results are extremely important, but prior research has failed to affirm that CSRI and integrated reports lead clearly and directly to CE strategies (Guranathne et al. 2021), which makes the present findings quite novel and significant.

In addition, AI-generated insights were incorporated into the theoretical framework to form an innovative approach. Data from social economy organizations were examined, and the four formulated hypotheses and the proposed model's predictive capacity were all confirmed. Notably, these results fail to agree with Lachuer and Ben Jabeur's (2022) conclusions. The cited authors conducted longitudinal analysis and found that CSR is negatively related to financial market performance. After apply-

ing AI tools, Lachuer and Ben Jabeur (2022) then observed that CSR exclusively improved the most sustainable companies' financial performance.

The current findings further highlight a persistent inconsistency when CE practices are incorporated into CSRR. CSR and integrated reports often remain focused on traditional environmental disclosures and lack the systemic orientation required by CE strategies. Gunarathne et al. (2021) similarly argue that CSRR alone does not guarantee the adoption of circular practices, which require a shift from linear to regenerative economic models. This gap between CSR and CE practices underscores the need to move beyond reporting for compliance and toward actionable sustainability strategies.

Critics have also suggested that CSR and integrated reports stop short of fully driving CE adoption. The voluntary nature of CSRR means that circular initiatives are often underreported or insufficiently embedded in strategic planning. The current research confirmed this disconnect while also providing evidence of how the integration of AI into CSR disclosure analysis can offer valuable insights into potential CE trajectories (European Commission 2022). The volume and sophistication of non-financial reporting have increased significantly over the past decade, especially given the GRI, Sustainability Accounting Standards Board, and the EU's Non-Financial Reporting Directive, among other initiatives. However, these disclosures often remain descriptive and fragmented and lack actions focused on circularity, frequently presenting sustainability as a peripheral concern rather than as a transformative business model, which inhibits the ability of CSRR to catalyze substantive integration of CE principles.

One of the issues identified by the present study is the absence of standardized, enforceable indicators specifically linked to CE practices. Many companies continue to report environmental data in linear terms without adopting lifecycle thinking or disclosing metrics related to material circularity, product durability, or resource regeneration. As a result, circular initiatives may be underreported or hidden within general sustainability narratives, weakening the CE's strategic visibility and organizational impact (Opferkuch et al. 2022).

Integrated reporting additionally often fails to link CSR goals with circular value propositions. Researchers have shown that even in sectors in which circular strategies are extremely important (e.g., manufacturing, agriculture, and textiles), reporting tends to focus on compliance or reputational aspects rather than systemic redesign, closure of material loops, or collaborative innovation. This instrumental use of CSRR, sometimes referred to as "green window-dressing," can create a disconnect between what is disclosed and what is implemented, ultimately undermining stakeholder trust and organizational learning.

Despite their potential benefits, CE practices are inconsistently incorporated into CSRR. Opferkuch et al. (2022) stress the need for comprehensive models that integrate all organizational activities by addressing the economic, social, and environmental affected by CE principles. The cited study aligns with the current findings, indicating the need for deeper integration of CE strategies and more consistent reporting practices. Transparency and accountability are crucial for the successful implementation of CE practices within CSR frameworks. Companies must openly report their sustainability actions to demonstrate their commitment to the CE. Mani et

al. (2016) and Marco-Fondevila et al. (2018) have voiced their support for the notion that transparency and accountability foster the adoption of CE practices.

Resource management is another critical area in which CSR and the CE intersect. The responsible management of natural resources is advocated by CE principles aligning with the CSR focus on reuse, recycling, and waste reduction. Geissdoerfer et al. (2017) and Scarpellini et al. (2019) assert that CSR practices facilitate the adoption of CE strategies by improving resource efficiency and minimizing environmental impact. Sustainable innovation driven by CSR is essential for the development and implementation of CE practices. CSR additionally encourages companies to innovate in ways that benefit society at large and the environment, which is fundamental for the CE. Adams et al. (2016) and Johansson and Henriksson (2020), in turn, indicate that innovation is a key driver of the closing of material cycles and enhancement of sustainability.

Commitment to stakeholders is a requirement shared by CSR and the CE. Effective collaboration with interest groups throughout the value chain is necessary to close material loops and achieve sustainability goals. Along these lines, Freeman and Dmytriyev (2017) stress the importance of stakeholder engagement in both CSR and CE strategies.

Managers also need to pay attention to the role AI can play in enhancing CSR and CE integration as AI tools facilitate the analysis of large datasets drawn from sustainability reports, identifying trends and predicting the impact of CSR policies on CE implementations. Lachuer and Ben Jabeur (2022) and Hauer et al. (2023) similarly advocate for the use of AI in improving transparency and accountability in sustainability reporting.

A further dimension of this debate is the relationship between CSR and financial performance. Lachuer and Ben Jabeur (2022) found that CSR is negatively associated with market performance in some contexts and benefits only the most sustainable firms, especially those supported by AI. The scope of the current research excluded assessing financial performance directly, but the results suggest that, in mission-driven organizations such as cooperatives and associations, integrating CSR and the CE enhances operational efficiency and stakeholder legitimacy even in the absence of direct market incentives.

The empirical validation of the proposed model offers a strong platform from which actionable pathways can be identified to strengthen the interplay between CSR and the CE. Rather than treating these concepts as parallel or loosely coupled domains, the findings confirm their potential mutual reinforcement, particularly when mediated by digital technologies and mission-oriented organizations. This insight suggests that the transition toward circularity is both a technical and strategic and cultural shift that involves the following five areas: transparency and accountability, resource management, sustainable innovation, stakeholder engagement, and AI tools.

First, transparency and accountability emerge as fundamental enablers. Organizations should choose to adopt CSR frameworks with credible reporting mechanisms in order to find a better position from which to communicate their circular actions, disclose material flows, and demonstrate the social and environmental value generated through CE initiatives. Transparent reporting fosters stakeholder trust and regulatory alignment, which are critical for scaling circular models. The present proposed model

highlights how the quality and structure of CSRI significantly affect the visibility and operationalization of CE practices.

Second, the findings stress the centrality of resource management as a bridge between CSR objectives and CE principles. CSR discourses are laced with mentions of responsible sourcing, product longevity, waste minimization, and resource regeneration—key tenets of the CE—but often lack executional clarity. The proposed model suggests that organizations that embed resource efficiency into their CSR strategy are more likely to internalize circular principles across their value chains, thereby achieving both environmental and reputational gains.

Third, this research underlined how sustainable innovation acts as a key mechanism through which CSR can accelerate CE adoption. Innovation in product design, service models, and logistics should be guided by social responsibility to facilitate closed-loop systems, reverse logistics, and life-cycle thinking. The results thus align with recent studies confirming that innovation should not be viewed merely as technological progress but as a socially-embedded process responsive to stakeholder values and long-term sustainability goals.

Fourth, stakeholder engagement proved to be both a CSR imperative and a necessary condition for successful CE implementation. The proposed model supports the idea that entities with stronger stakeholder dialogue—whether with suppliers, clients, communities, or policymakers—are better equipped to enact collaborative circular strategies. These tactics may include the co-design of sustainable products, shared responsibility for take-back systems, or multi-actor platforms for resource sharing. The findings suggest that social capital generated by CSR can be strategically leveraged to overcome systemic resistance to circular change.

Last, AI tools function as a critical accelerator. AI technologies enhance organizations' capacity to extract, classify, and interpret vast volumes of unstructured CSR data, thereby enabling better diagnostics, scenario modeling, and forecasting of circular actions. AI can act as a catalyst, operationalizing the CSR-CE nexus by turning qualitative disclosures into quantifiable insights. These tools also facilitate adaptive learning, which allows organizations to adjust their circular strategies in real time based on performance feedback and emerging risks. The validated model reveals the theoretical links between CSR and the CE and provides pragmatic entry points for their integration. These opportunities include reinforcing data-driven transparency, embedding resource strategies into CSR, innovating within stakeholder ecosystems, and using AI to close the loop between intention and impact. This study thus contributes not only to academic discourse but also to managerial and policy-oriented agendas by defining roadmaps for more coherent, effective CSR-CE integration.

In addition, the present research incorporated ANN analysis to assess the model's predictive capacity and explore potential non-linear patterns. The results were compared to the PLS-SEM findings. The ANN models failed to outperform PLS-SEM in terms of predictive accuracy, with the two approaches yielding extremely similar results for key metrics such as R^2, RMSE, and MAE. This convergence further confirms the empirical robustness of linear models and suggests that the relationships among CSR constructs and CE orientation are predominantly linear.

Removing barriers and offering incentives are vital steps toward incorporating CE practices. Cultural, market, regulatory, financial, and technological obstacles must

be overcome to enable the adoption of circular strategies. Kirchherr et al. (2018) and Delouyi et al. (2023) similarly confirmed that identifying and addressing these barriers significantly promotes the implementation of CE principles.

6 Conclusion

6.1 Conclusions

The model was grounded in an explanatory framework that clarified the relationships among variables, after which its predictive performance was evaluated. The results thus provide valuable insights into how AI can be used to predict circular initiatives in Spain's social economy. The findings comprehensively respond to the research goals and validate the hypotheses, reinforcing the theoretical and practical links between CSR and CE strategies. The first research objective focused on understanding organizations' CE orientation based on their CSRI, and the results clearly show that access to CSRI directly and positively influences the implementation of CSRAs. This finding addresses RQ1 and RQ2 by confirming that CSR and the CE are interconnected concepts and that CSRR is not merely informative but also strategic as it influences how organizations act. These conclusions align with prior studies that have suggested transparency and responsibility are precursors to sustainability-oriented behaviors.

This research also confirmed that the implementation of CSRAs facilitates the identification of barriers that limit the CE, as well as the incentives that promote it. The results include that aligning CSR with CE principles fosters better resource management by encouraging reuse, recycling, and waste reduction. Companies that prioritize CSR are more likely to adopt CE strategies, which significantly minimize these organizations' environmental impact and enhance resource efficiency. This alignment fosters a more sustainable approach to business operations through a focus on economic, social, and environmental objectives.

In addition, the conclusion was reached that identifying BICE contributes directly and positively to the incorporation of CE strategies—although to a less significant degree. Overcoming barriers, such as technological challenges and financial constraints, is essential for a broader implementation of CE principles. Concurrently, incentives (e.g., regulatory support) and market-driven initiatives can significantly enhance the adoption of CE practices. However, further research is needed to explore the nuanced dynamics of these relationships and their implications for CSR.

CSR incentivizes organizations to develop and implement innovative solutions that benefit both society at large and the environment. These innovations are vital for the advancement of the CE as they encourage the development of new products and processes that maximize material reuse and minimize waste. The findings confirm that access to CSRI is directly and positively associated with the use of CE strategies. This study further highlighted the importance of stakeholder engagement in promoting the CE through CSR. Effective CSR practices need to involve a diverse range of internal and external stakeholders. Engaging these actors is equally critical for the success of CE practices as collaboration must occur across the value chain to close material loops and achieve sustainability goals. In this way, the proposed model suc-

cessfully links CSRI with CE orientation and shows that the relationship is mediated by the implementation of CSRAs and the identification of BICE. The results provide empirically robust support for the validity of H1, H2, H3, and H4 and insightful responses to RQ3, RQ4, and RQ5.

The second research objective was to develop a predictive model using PLS-SEM and AI tools, which was fully achieved. The results underscore the potential for employing AI in predicting and enhancing CE initiatives. AI technologies can optimize resource management, enhance waste sorting and separation, and provide valuable insights into market trends and resource consumption patterns. These capabilities are crucial for overcoming technological and financial barriers, which in turn facilitates CE transitions. Notably, using AI reinforces the proposed model's predictive power—as suggested in RQ6—confirming the importance of AI as useful technology and as a facilitator of sustainability transformations. AI is able to analyze large volumes of data and generate insights that support decisions, so it is essential for anticipating and managing CE-related dynamics.

This study additionally verified the theoretical pathway proposed in the conceptual model: CSRI → CSRAs → identification of BICE → CE strategy. This chain of effects shows how intangible factors such as information and culture can lead to tangible sustainability outcomes, which comprises a novel contribution to the literature on responsible management in the social economy.

The results further offer important insights into social economy enterprises, a population often underexplored in CE research. These organizations' unique governance configurations and values-based mission make them ideal candidates for CE innovations, and their CSR practices can drive structural change toward greater sustainability. The findings thus add to the existing evidence and complement broader studies conducted in different sectors and regions.

However, this research underlines the importance of context. The results are derived from Spain's Extremadura region, which has specific socioeconomic conditions that must be considered when generalizing the findings. Future studies need to replicate the model in different regional or national contexts in order to improve the present results' external validity and capture regional variations in CE adoption.

The findings also emphasize that removing key barriers, especially technological and financial ones, and reinforcing strategic incentives, such as regulatory support, innovation frameworks, and stakeholder collaboration, are essential for the full implementation of CE practices. These insights reinforce the idea that CSR is both a precursor of and a platform for broader systemic transformation, through which the CE becomes an operational extension of responsible business conduct.

Finally, the comparison of the PLS-SEM and ANN results revealed that, when a linear model (i.e., PLS) and a non-linear model (i.e., ANN) yield similar Q^2 values, the relationship between the predictors and outcomes is essentially linear or at least adequately captured by PLS-SEM. This part of the analysis ascertained that PLS-SEM provides theory-driven causal validation, while ANNs complement this by detecting potential complex, non-linear relationships and reinforcing predictive power. However, the findings stop short of justifying the use of neural networks because the latter failed to improve the Q^2 or R^2 values. The simpler model (i.e., PLS-SEM) is preferable as it is more stable and easier to interpret.

6.2 Implications

The findings generated by this research have three types of implications: theoretical, practical, and managerial. Each category is discussed below in detail.

6.2.1 Theoretical implications

This study sought to expand the literature by using AI tools (i.e., SEM) to predict the implementation of CE initiatives in the social economy. On a theoretical level, the research expanded the relevant fields by being the first to link CSR, the CE, and the analytical capabilities of AI—an approach that has been rarely applied in previous investigations. The proposed model provides a better understanding of the causal relationships between organizational factors and the adoption of circular practices, which offers a solid conceptual basis for future interdisciplinary studies. This conceptual articulation comprises an explanatory framework that can be replicated or adapted to fit different business or geographical contexts, which further increases the theoretical value of the findings.

An additional theoretical contribution is that this study included AI not only as a supporting methodology but also as a conceptual bridge between data-driven analysis and sustainability theory. By integrating AI, the research showed how predictive analytics can explain and anticipate organizational behavior involving circularity, thereby enriching the available theoretical models of responsible management and sustainability transition. This result provides empirically robust support for adding AI is a core element to the evolving field of CSR-CE research and confirms that AI can contribute to a more dynamic, anticipatory understanding of how companies move from linear to circular models.

6.2.2 Practical implications

From a practical perspective, the proposed model allows social economy managers to identify more precisely the internal factors that favor the implementation of CE practices, which should facilitate more informed strategic decision making. Companies can use these findings to reorient their CSR policies toward more effective, sustainable actions; optimize resources; and anticipate obstacles in transitions to circular practices. Using AI as a management support tool can further strengthen organizations' ability to improve continuously. Taken together, the results are of direct practical value because they link data analysis with strategy formulation, thereby increasing operational sustainability and transforming production models in the social economy.

More specifically, this research demonstrated how AI-based predictive modeling can serve as a strategic tool in decision-making processes. Managers can identify which CSR variables most strongly predict circular behaviors in order to allocate resources more efficiently, prioritize impactful initiatives, and monitor progress toward circular business objectives. The present findings both enhance the effectiveness of CSR strategies and provide a real-world roadmap for how to accelerate the shift from linear to circular production systems. The proposed model, therefore, is a

practical instrument for embedding predictive intelligence into sustainability management processes.

6.2.3 Managerial implications

The predictive methodology based on AI offers valuable insights into the ways social economy enterprises can optimize their CSR strategies and accelerate their CE transitions. The model helps identify which circular actions are most likely to succeed based on organizational characteristics and thus facilitates strategic decision making. For instance, managers can prioritize investments in initiatives with greater impact or feasibility, such as material reuse or the implementation of sustainable supply chains.

In addition, analyzing predictive patterns could reveal common barriers to adopting circular practices, which companies can then anticipate and counter with more effective mitigation policies. This approach can also be integrated into continuous monitoring and control systems, allowing CSR policies to be adjusted dynamically in response to internal objectives and changes in socioeconomic environments. Overall, this research should be valuable to managers because it provides actionable intelligence that supports proactive, data-informed decision making and the institutionalization of circular practices.

These theoretical and practical contributions underscore the dual role of AI in this context. First, AI-based methods enhance the predictive power of sustainability studies. Second, AI is a strategic resource for organizations that want to design, implement, and monitor their transition into CE strategies. Integrating AI within CSR-CE frameworks comprises a significant step forward toward understanding and managing sustainability through data-driven innovation.

6.3 Limitations

This study had four limitations that need to be considered when planning future research. First, the sample of 129 companies was sizable, but it fell short of representing all Spanish entities, which limits the generalizability of the findings as they cannot be easily applied to international contexts or different industries. Second, the geographical limitations were substantive. Socioeconomic and political conditions clearly vary by region in Spain, so the sample's restriction to the region of Extremadura means the results should not be directly applied to all Spanish regions.

Third, the data lacked depth as the questionnaire responses may not have captured the complexity and nuances of companies' CSR and CE initiatives. Last, the comparative analysis relied on neural networks, but the data had shortcomings, namely, a restricted number of predictors and restricted information. This limitation could explain why the more complex models (i.e., ANN1 and ANN2) failed to outperform the linear model (i.e., PLS-SEM). The nearly identical Q^2 values also suggest that the additional complexity of the neural networks prevented them from providing any additional predictive value.

Given these shortcomings, the present findings should be interpreted with caution, and future research should address and mitigate these challenges. First, follow-up studies should consider increasing the sample size and diversifying the profile of

participating entities to enhance the generalizability of the results. Conducting stratified sampling by sector, size, or organizational model may further ensure a broader representation of Spain's social economy enterprises. Second, the geographical scope needs to extend beyond Extremadura to capture regional differences across Spain and better understand how socioeconomic, cultural, and institutional contexts influence the implementation of CSR and CE practices. Third, researchers should also conduct comparative cross-regional or even international analyses to explore the influence of national policies, market maturity, and institutional support on the spread of CE strategies among socially responsible enterprises.

Fourth, longitudinal studies could also provide insights into how circular practices evolve over time and the factors that drive or hinder their consolidation. Fifth, to ensure deeper data, qualitative approaches could be applied, such as in-depth interviews, case studies, or focus groups. These methods would allow scholars to capture the complexities, motivations, and challenges faced by organizations when implementing CSR and CE initiatives—elements that often remain hidden in quantitative surveys. Last, the performance of ANNs could be enhanced in future research by incorporating a larger number of predictors, interaction terms, or more complex datasets in which non-linearity plays a genuinely significant role.

The originality and value of the proposed model lies in its integrative, sequential approach, which connects CSRI with the implementation of CE strategies via a structured path that includes CSRAs and the identification of BICE. Previous studies have often treated CSR and the CE as separate or parallel frameworks, but this model offers a novel structure that positions CSRI as both a communication tool and a predictive and catalytic element in sustainability transitions. The use of AI and PLS-SEM additionally strengthens the robustness and applicability of the model by providing a data-driven mechanism that forecasts CE orientation in social economy organizations. This fresh approach advances the theoretical understanding of the CSR-CE nexus and offers organizations a practical, replicable model with which to assess and improve their sustainability strategies. The proposed model also fills a gap in the literature on social economy enterprises, thereby expanding the scope of sustainability research to a category of organizations deeply committed to social and environmental values. The present study thus enriches an extremely important emerging line of research.

Appendix: Items measuring model constructs

Measurement scales of different constructs

Indicators (validated in the model) based on Scarpellini et al. (2019); Aranda-Usón et al. (2020); Scarpellini (2022); and Gallardo-Vázquez et al. (2024a, b, c)

CSRI

CSRI1: Our level of knowledge about the SDGs and 2030 Agenda has increased considerably in the last five years

CSRI2: Our organization has integrated sustainability and the SDGs into its corporate strategy

CSRI3: This organization has a person/department working on sustainability strategies

CSRI4: Our organization's corporate strategy includes the identification of priority SDGs
CSRI5: Our work toward sustainability and the SDGs has produced competitive advantages for us
CSRI6: The visible impacts on our organization have led us to continue with initiatives focused on sustainability and the SDGs
CSRI7: We believe that this organization will achieve better performance as it progresses toward implementing the 2030 Agenda

CSRA

CSRA4: We are able to promote healthy lifestyle habits that contribute to employee health and well-being
CSRA5: We have opportunities to contribute to quality staff education
CSRA6: Our organization promotes female workers' personal development and contributes to gender equality
CSRA8: We recognize the importance of establishing alliances for achieving the SDGs
CSRA9: This organization makes investments that lessen the environmental impact of its activities
CSRA10: Our organization carries out waste recycling measures
CSRA11: This organization redesigns products and/or services to increase their functionality

BICE

BICE1: One barrier to the implementation of CE practices is no training programs to develop the specialized personnel necessary for CE strategies
BICE 2: As incentives for CE practices, we offer subsidies or bonuses for implementing the relevant changes
BICE3: Other incentives include citizen awareness and information dissemination campaigns

CE

CE1: Our organization's management is directly involved in circular economy issues
CE2: The implementation of CE principles is considered a priority by this organization
CE3: Our organization communicates its environmental policy and CE initiatives to all staff members
CE4: This organization offers staff training in CE practices
CE5: Our organization is able to meet the demand for new professionals whose profiles fit with the CE
CE6: The CE inspires greater collaboration among our workers in the sharing of goods and services
CE7: The CE involves new training in environmental topics

CSR = corporate social responsibility; CSRI = CSR information; SDGs = Sustainable Development Goals; CSRA = implementation of CSR actions; BICE = barriers and incentives to circular economy (CE)

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Data availability The data that support this study's findings are available from the corresponding author upon request.

Declarations

Conflict of interest The authors declare no potential conflicts of interest with respect to the research, authorship, and publication of this paper.

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