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Can (A)I help you measure your circularity? An AI-driven and collaborative framework for strategic KPI definition

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ABSTRACT

The measurement of circularity is becoming increasingly important in steering companies toward more sustainable production models. Grounded in socio-technical systems (STS) theory, this exploratory multiple-case study investigates how to enhance the processes of defining KPIs for assessing corporate circularity, with particular attention to artificial intelligence (AI) and managerial collaboration. Based on ten case studies of circularity-related KPIs development, the research employs fuzzy set qualitative comparative analysis (fsQCA) to examine how different approaches to constructing KPI sets affect their perceived effectiveness, as evaluated by experts. The findings indicate that AI, internal and external collaboration may support the development of KPI sets. Drawing on these findings and insights from an expert workshop, the paper proposes a framework for measuring corporate circularity through AI. The paper offers contributions to both managerial practice and theoretical understanding by analyzing the interplay between managers and AI in defining measurement instruments and KPIs, connecting these insights to STS theory.

1. Introduction

The growing environmental issues highlighted by the breach of several planetary boundaries have underscored the limitations of the current development model and the need to rethink it (Desing et al., 2020). In this context, the concept of sustainable development is becoming increasingly relevant, particularly in reconsidering production and consumption models. Recently, the paradigm of the circular economy has emerged within this framework (MacArthur, 2013). This paradigm aims to facilitate the transition to an industrial economy that is deliberately restorative and seeks to imitate nature by actively refining and optimizing the systems in which it operates (Mhatre et al., 2021; Velenturf and Purnell, 2021).

In this scenario, the identification and implementation of circular practices and/or the adoption of circular business models (Nandi et al., 2020) by companies are crucial to supporting the transition (Lanaras-Mamounis et al., 2022; Saidani et al., 2017). In particular, the importance of relying on data to implement circularity strategies within companies is emphasized by numerous studies as a preliminary stage for the proper identification of such strategies (Saidani et al., 2017, 2019; Valls-Val et al., 2022). In recent years, a multitude of research has emerged on the topic of measuring circularity (D'Adamo et al., 2024; Kostakis and Tsagarakis, 2022; Valls-Val et al., 2022). These studies highlight the fact that it would be incredibly challenging for a company to gather accurate information without a process for tracking their performance towards circularity. Consequently, they propose either sets of KPIs or measurement tools composed of multiple indicators and combinatorial logics to obtain an overall assessment of circularity. The topic has expanded so rapidly that today there is a multitude of studies proposing both sector-specific KPI sets (Hussmo and Skärin, 2024) and tools to measure circularity performance (Sacco et al., 2021) in connection with various company functions (Corsini et al., 2024).

At the same time, the transition towards a circular model in companies is undoubtedly supported by numerous technologies that can be seen as enablers (Del Vecchio et al., 2022; Pan et al., 2023; Sharma et al., 2023), including AI (Dhanya et al., 2023). AI is becoming a tool capable of revolutionizing entire industrial sectors, as well as transforming how certain practices and activities are conducted within companies (Ecer

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and Torkayesh, 2022; La Torre et al., 2023). AI has for instance the potential to facilitate data-driven decision-making and support process innovation. However, the role of AI as a tool for supporting the measurement of circularity performance remains highly relevant yet insufficiently explored in academic research.

Our study pursues a dual objective: first, to bridge the practical research gap by investigating whether and how AI tools can facilitate the measurement of business circularity; and second, to situate the measurement of circularity assisted by AI tools within the conceptual frameworks that elucidate the relationship between humans—particularly managers—and AI, focusing on the socio-technical systems theory (STS) (Appelbaum, 1997; Trist, 1981). Specifically, the paper is based on empirical exploratory research aimed at evaluating sets of circularity KPIs developed for ten companies operating in different sectors. Some of these KPI sets were developed through action research processes involving various company functions, including R&D teams and researchers. Others were created using AI, while some resulted from collaborative efforts among companies, researchers, external organizations, and AI. These KPI sets were subsequently evaluated by interdisciplinary experts based on predefined criteria. The different combinations used to develop the KPI sets were compared with the evaluations obtained and analyzed using fuzzy-set Qualitative Comparative Analysis (fsQCA). The analysis highlights configurations that explain a level of evaluation, including those in which AI is present. Based on the results of the analysis and a subsequent workshop conducted with selected experts, the paper outlines a framework for using AI to support the measurement of circularity in companies.

The contributions of this research are manifold. On one hand, through an experimental analysis, we demonstrate that AI can be a useful tool to support management in designing KPI systems for measuring circularity within companies. On the other hand, based on the empirical evidence collected, the work proposes an operational framework for utilizing AI as a tool for measuring circularity in companies, drawing on the results of interviews and analysis of the relevant literature on the topic.

2. Theoretical background and literature review

2.1. Socio-technical systems theory for analyzing AI-management collaboration

STS focuses on examining the connections between an organization's social elements—such as individuals, their interactions, relationships, and the organizational framework—and its technical elements, which include technology, knowledge, processes, methods, and equipment that may influence organizational performance (Appelbaum, 1997; Trist, 1981; Walker et al., 2008). The theory posits that social and technical components are interdependent, meaning that solely introducing technological innovations or improvements does not directly translate into performance enhancement if the social aspects are not aligned (Baxter and Sommerville, 2011; Trist, 1981). In other words, focusing solely on either the social or technical aspects of an organization can limit its overall effectiveness (Thomas, 2024). Therefore, the objective is to develop organizational systems that support both human and technical elements, fostering adaptability while maintaining predictability and stability (Walker et al., 2008). Consequently, as remarked by Münch et al. (2022) when integrating new technologies, it is essential to assess both social considerations and technological challenges.

This framework has been increasingly adopted in recent years to understand and explain interactions between managers/employees and AI (Chowdhury et al., 2022; Herrmann and Pfeiffer, 2023; Makarius et al., 2020). Makarius et al. (2020) have even proposed a socio-technical AI socialization framework, drawing from STS as an approach to strategically optimize collaboration between technology and employees to enhance business economic performance. Utilizing perspectives from STS, Herrmann and Pfeiffer (2023) refine the typical concept of "human-centered AI" claiming that for AI to be effectively integrated into decision-making and operational processes, it is vital to involve not only individuals but the entire organization, encompassing organizational processes, management practices, and the decision-making frameworks that govern the interaction between humans and machines.

Numerous studies have documented various applications of AI technologies in corporate settings (Chowdhury et al., 2022; Daugherty et al., 2019; Haenlein and Kaplan, 2019), spanning from automating simple, repetitive manual tasks to developing autonomous systems capable of functioning and making decisions independently of human input. However, the human-AI combination that generates the highest socio-technical capital occurs when there is a deep level of symbiotic involvement between humans and machines, enabling co-creation (Makarius et al., 2020). The STS theory framework is highly valuable in this context, as it can help explain how high socio-technical capital is generated through co-creation. However, research on this topic is still in its early stages, and empirical evidence remains limited (Chowdhury et al., 2022).

STS theory, initially conceived as comprising only two systems (Trist, 1981)—the technological and the social—has been expanded to include the environmental system in which an organization operates (Kull et al., 2013). Specifically, an environmental system is defined as encompassing governmental, economic, industrial, and research entities relevant to the organization. In this context, socio-technical systems emerge from the interaction of social, technical, and environmental systems, shaping organizational outcomes (Botla and Karaca, 2018). In exploring the role of AI within the STS framework, there is still a lack of analysis on how external collaborations, such as those between managers and external actors, including the research community or other organizations within the same sector, can contribute. Current studies often highlight the need for coordination among these actors or emphasize the importance of regulating and managing interactions with external stakeholders (Herrmann and Pfeiffer, 2023), yet they do not provide concrete evidence of their effects.

In this specific analytical context, initial evidence suggests that AI can serve as a valuable resource for defining and configuring KPIs within a business context, thereby aiding management in strategy development (Kiron et al., 2024; Schrage et al., 2023). However, the complex interaction between social and technical and environmental aspects in achieving optimal KPIs remains underexplored. Thus, this paper aims to investigate circularity measurement as a case study, examining how the design of synergies and procedures must align both the integration of AI-generated outputs and the active participation of individuals.

2.2. Measurement in the context of the circular economy

The measurement of circularity levels is a hot topic at this point in time. With the advent of numerous policies and regulations pushing companies to implement circular economy initiatives (Marino and Pariso, 2021), they need KPIs and tools that can facilitate the assessment of circularity performance and, consequently, support their transition (Vinante et al., 2021). In this context, numerous circularity metrics, KPIs, and tools have indeed been developed by the scientific community, NGOs, and other actors more closely connected to the consulting world (Saidani et al., 2017, 2019). While there is a clear need to standardize KPIs for measuring circularity (Valls-Val et al., 2022) a company must ensure that the identified KPIs are specific to its sector and capable of capturing industry-specific characteristics. Among the most recent developments in circularity measurement, the ISO 59020:2024 standard (ISO, 2024), seeks to provide a standardized framework for assessing circularity performance while allowing companies the flexibility to define additional indicators. This flexibility is justified by the fact that, according to ISO 59020:2024, organizations may have different needs based on their specific circularity goals, industry, and context. In this context, the process of creating KPIs for measuring circularity becomes critically important from a practical perspective for companies.

Although research on the subject is becoming substantial, a significant gap remains between academic research on circular economy indicators and the needs of industry (Urain et al., 2024). In fact, much of this academic research is focused on analyzing pre-existing tools (Valls-Val et al., 2022) and conducting literature reviews (Urain et al., 2024), which offer little concrete help to companies in formulating circularity KPIs. Some authors emphasize the need to support the development of indicators that are tailored to the needs and realities of businesses, adopting a holistic approach to functional business areas and capable of measuring all phases of the life cycle, while being easy to implement (Urain et al., 2024).

In this context, our study aims to analyze an STS framework for measuring corporate circularity by integrating AI technology within organizational processes. Grounded in STS theory, this framework recognizes that AI's effectiveness in defining circular KPIs depends on its integration with the expertise of the social system and collaborative decision-making processes, including interactions with external actors. Specifically, we propose the following proposition:

The integration and alignment of AI with internal cross-functional collaboration and the involvement of external actors leads to the development of comprehensive and strategically relevant KPIs, facilitating effective circularity measurement at the corporate level.

3. Methods

Our study adopts a multiple case study approach that integrates both qualitative and quantitative methodologies. In detail, the research is grounded in ten case studies of companies that developed KPIs to measure corporate circularity. These KPIs were created through three distinct approaches: some were developed with the support of researchers but without AI, others with the assistance of AI, and a subset exclusively by AI. The resulting KPI sets were subsequently assessed by circular economy experts from academia and consultancy (practitioners). The evaluations served as main output variables for an fsQCA analysis, enabling the identification of optimal configurations for crafting effective and strategically relevant KPI sets. Consistent with fsQCA guidelines that recommend 10–15 cases to explore novel phenomena (Lu et al., 2020), we purposefully selected ten companies spanning manufacturing and services. Moreover, as highlighted in numerous studies, results from fsQCA are more comprehensive when quantitative methodologies are combined with qualitative approaches to better interpret the findings (Lu et al., 2020; McDonald et al., 2015). For this reason, the individual evaluation results and the fsQCA findings were analyzed and discussed in a workshop with experts, offering deeper insights into the nature of the indicators and their strategic relevance. Finally, the evidence gathered during the research process contributed to the development of a framework for measuring circularity using AI tools. Fig. 1 summarizes the multi-stage research design adopted.

3.1. *Circular KPI sets*

A total of ten case studies were employed to meet the study's objectives. These cases were selected using a purposeful sampling strategy designed to capture sectoral diversity and a range of potential KPIs and circular economy measurement approaches. Data were gathered through participant observation (i.e. in cases 1 to 8) and non-participant observation (i.e. in cases 9 and 10) during KPI development workshops conducted in the ten companies, as well as through a systematic analysis of the firms' internal KPI design documents.

The ten case studies, along with their respective NACE codes and classification descriptions, are presented in Table 1.

The KPI sets for each of the ten companies were developed using different approaches. Some were created through action research processes involving collaboration between academic researchers and companies. Others incorporated AI (ChatGPT 3.5/ChatGPT 4.0) as a tool to support the creation of KPI sets, while some were developed with additional input and consultation from external actors, such as other companies operating in the same sector (see Appendix 1). In one case, the KPIs set was developed exclusively using AI to evaluate whether AI

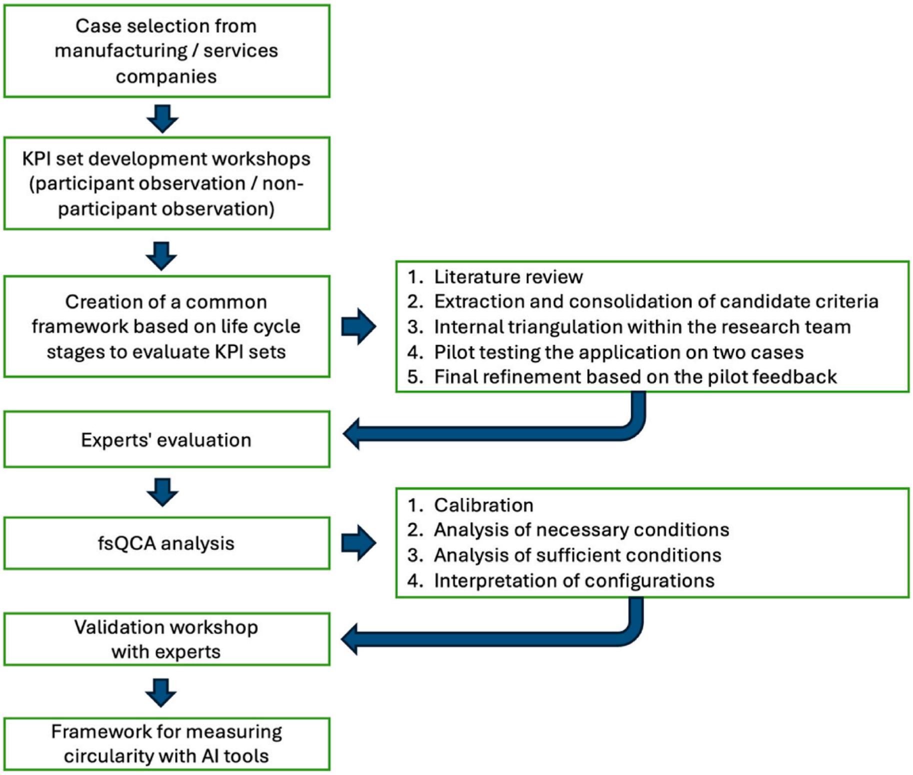

Fig. 1. Multi-stage research design.

Table 1
Overview of the ten company types involved in the case studies.

ID	Sector of the company	NACE code	NACE Description
1	Chemical manufacturing	20.13	Manufacture of other inorganic basic chemicals
2	Water resource management	36.00	Water collection, treatment and supply
3	Footwear production	15.20	Manufacture of footwear
4	Automotive parts manufacturing	29.32	Manufacture of other parts and accessories for motor vehicles
5	Apparel and textile production	14.19	Manufacture of other wearing apparel and accessories
6	Information technology services	63.11	Data processing, hosting and related activities
7	Construction materials	23.61	Manufacture of concrete products for construction purposes
8	Steel production	24.10	Manufacture of basic iron and steel and of ferro-alloys
9	Food production	10.72	Manufacture of rusks and biscuits; manufacture of preserved pastry goods and cakes
10	Sports management and operations	93.12	Activities of sports clubs

alone could generate effective KPI sets.

For the KPI sets created in collaboration with companies (see Appendix 1), the process involved numerous exchanges, including workshops, interviews, and discussions. These exchanges allowed companies to refine the KPI sets to ensure their alignment with the specific needs of the industry sector.

A common framework based on life cycle stages, sourcing, design, production, distribution, use, and waste management, was applied to all KPI sets. Indicators were assigned to the most appropriate phase, leveraging the validity of this life cycle approach, as highlighted by several authors (Gheewala and Silalertruksa, 2021; Kirchherr et al., 2023; Neligan, 2018) and endorsed by the European Commission (European Commission, 2018). This framework ensured consistency across all ten cases. To facilitate comparison among the ten cases, an average of 30 indicators per KPI set (±5 %) was established. This number was deemed sufficient to provide a reliable and comprehensive representation of business circularity levels.

3.2. Evaluation of KPI sets

3.2.1. Criteria for the evaluation

For the evaluation of the KPI sets developed for this study, it was essential to identify criteria for submission to the expert panel, guiding their assessment. The pool of evaluation criteria was generated through a five-step procedure: (i) a literature review, (ii) extraction and consolidation of candidate criteria, (iii) internal triangulation within the research team, (iv) pilot testing the application on two cases, and (v) final refinement based on the pilot feedback.

The literature review was conducted to identify established frameworks, such as SMART goal setting (Shahin and Mahbod, 2007), along with insights from literature on circular economy metrics and tools (e.g. Khan and Kabir, 2020; Pavan and Todeschini, 2009; Roos Lindgreen et al., 2020).

During the extraction and consolidation phase, the SMART framework was chosen as the foundation for evaluating the KPIs, incorporating dimensions such as specificity, measurability, attainability, relevance, and time-bound definitions. Additionally, building on Roos Lindgreen et al. (2020), certain criteria were tailored to correspond with circular economy phases (i.e., sourcing, design, production, distribution, use, and end-of-life).

The five-step process resulted in the identification of eight criteria. Three of these were phase-specific and were applied consistently across all circular economy phases. These included: ease of data retrieval, objectivity of representation, and comprehensiveness of coverage (Khan and Kabir, 2020; Pavan and Todeschini, 2009; Roos Lindgreen et al., 2020). Set-wide criteria were also established to assess the KPI sets in their entirety. These included: coverage of core circular economy dimensions, sector suitability, strategic decision support, time-sensitivity, and alignment with corporate priorities (Khan and Kabir, 2020; Pavan and Todeschini, 2009; Roos Lindgreen et al., 2020; Valls-Val et al., 2022).

The criteria were organized into a standardized evaluation template for each KPIs set used to measure circularity levels across various industry sectors (see Appendix 1). The template employs a 1–7 Likert scale, where 7 represents the most desirable or positive option and 1 the most negative.

3.2.2. Experts involved in the evaluation

To evaluate the KPI sets, we engaged six interdisciplinary experts in Economics and Finance, Environmental Law, Sustainability Management and Reporting, Engineering and Design (two experts), and Sustainability Management (see Appendix 2). The number of experts involved aligns with similar studies that rely on expert evaluations (El Baz et al., 2022; Payer et al., 2024). The experts involved in the review of the KPI sets were selected based on several criteria. First, they possessed a strong educational background in disciplines related to the circular economy and operational experience in applying circular economy principles within industrial contexts or through applied research. To ensure a comprehensive perspective, it was essential to include experts with diverse professional backgrounds, spanning both academia and consultancy. Lastly, the selected experts demonstrated strong analytical skills and the ability to critically evaluate the relevance, feasibility, and effectiveness of the proposed KPI sets across various sectors.

Candidate experts were identified and invited through a standardized call for participation, which included an abstract of the study, a detailed timeline, and instructions. One week prior to the scoring phase, panelists participated in a 45-minute online briefing to review the study objectives, evaluation criteria, and the 1–7 Likert scale. Each expert then independently completed a standardized scoring template, submitting their ratings anonymously via an online form.

After collecting the expert evaluations, we assessed the consistency of their responses by calculating Cronbach's α on the eight item-level ratings. The resulting $\alpha = 0.80$ indicated good internal consistency among the criteria. Given the deliberate heterogeneity of the panel, a high overall intraclass correlation was not expected; indeed, the ICC(2, k) for the composite scores was 0.27. Previous studies in various fields suggest that while consensus is central to different forms of expert evaluation, definitions of consensus vary considerably and are often poorly documented, particularly in multidisciplinary panels (Bornmann et al., 2010; Mutz et al., 2012; Schifano and Niederberger, 2025).

We thus assessed the ICC within each core-expertise subgroup. We found that the two Engineering and Design experts achieved ICC(2,2) = 0.74, and the two Sustainability-focused experts (Sustainability Management and Reporting, and Sustainability Management) achieved ICC (2,2) = 0.66. Both figures indicate substantial agreement. These domain-specific reliability estimates demonstrate that experts with overlapping backgrounds produced evaluations that were consistently aligned.

3.3. Data analysis

To conduct a comparative analysis of the methods used to develop KPI sets and their overall performance, as evaluated by experts, we employed a fsQCA (Ragin, 2008; Rihoux and Ragin, 2009). This methodology is based on Boolean algebra and fuzzy set theory; it is particularly well-suited for identifying distinct configurations that, while not mutually exclusive, converge on a uniform conclusion. fsQCA is generally regarded as a qualitative-quantitative methodology, especially because it integrates inductive qualitative insights with empirical quantitative assessments. In our study, we used the fsQCA 4.1 software developed by Ragin and Davey to perform the analysis (Ragin and Davey, 2023).

The fsQCA uses condition variables to understand how they can influence the achievement of an outcome variable. In our study, the condition variables are represented by the methods used to construct the KPI sets, while the outcome variable is represented by the average of the expert evaluations of the KPI sets (Table 2). The table input of the fsQCA is presented in Appendix 1.

The outcome variable in our study is the only fuzzy variable, which requires a calibration process. During this process, calibration rules transform the variable into membership scores (ranging from 0 to 1), indicating the degree to which cases belong to particular outcome sets. For the calibration, we followed the rules suggested by Ragin, which involve identifying three distinct markers: a full membership threshold, a full non-membership threshold, and a cross-over point (Ragin, 2008). The calibration was performed using the fsQCA 4.1 software, with the 95th, 50th, and 5th percentiles of the sample chosen as thresholds, as seen in similar studies (Nikou et al., 2024). Although some studies suggest alternative approaches to calibration using Likert scales ranging from 1 to 7 (Schmitt et al., 2017), in our case, the experts' judgments were very close to each other, making such approaches less appropriate. Therefore, the use of the percentile-based approach was deemed more suitable. For the outcome variable, full membership is set at 5.592, the cross-over point at 5.219, and full non-membership at 4.786.

3.4. Data quality assessment

To mitigate the risk of subjectivity typically associated with studies based on limited data, we organized a workshop with the experts involved to conduct a verification and triangulation of the data used in the fsQCA. In particular, during the workshop, we presented the definitions of the conditions, the truth table, and the two sufficient pathways to the experts, who confirmed the accuracy of the definitions, discussed and commented on the plausibility of the identified solutions (see Discussion section).

Moreover, considering that the calibration was conducted with reference to other studies but that the sample size was rather limited, we tested the results following Ragin's (2008) suggestions, using alternative anchors for the direct calibration. In particular, we used the 90th, 50th, and 10th percentiles of the sample as thresholds, as well as the maximum value, the 50th percentile, and the minimum value of the sample as thresholds. In both cases, we obtained the same results, with an unchanged solution coverage and solution consistency.

Finally, we re-estimated the truth-table minimizing algorithm, incrementally raising the consistency cut-off from 0.80 to 0.85. The same three sufficient pathways emerged in every run, with an unchanged solution coverage and solution consistency.

Table 2
Outcome and conditions.

Type of variable	Name	Description	Codification
Outcome	Evaluation	Average of expert evaluations.	Fuzzy value
Condition	Collaboration	Internal collaboration among various company functions to define circularity KPIs.	Crisp
Condition	ReDinvolvement	Involvement of the company's R&D function to define circularity KPIs.	Crisp
Condition	AI	KPI set entirely generated with the help of AI	Crisp
Condition	External	Contribution of representative of external companies in the development of the KPI set.	Crisp
Condition	Research	Collaboration with universities to develop the KPI set for measuring circularity.	Crisp

4. Results

Drawing on the data gathered concerning how the KPI sets were developed, together with the corresponding evaluations provided by the six experts, this section presents the results of the fsQCA analysis. In detail, we conduct a two-tier analysis, first testing for necessary conditions and subsequently analyzing sufficient configurations that lead to the observed outcome. The analysis of necessary conditions is extremely important to verify that a given condition is indispensable (i.e., always present whenever the outcome of interest occurs) (Dul, 2016). The consistency and coverage of each causal condition in the analysis of necessary conditions are presented in Table 3. For a causal condition to be defined as necessary, it must exceed 0.90 in consistency and 0.75 in coverage (Ragin, 2008).

As illustrated in Table 3, the consistency and coverage levels for each condition fell below the recommended threshold, suggesting that the condition variables were insufficient to fully account for the outcome variable.

We then carried out the analysis of sufficient conditions to identify which combinations of conditions are sufficient, meaning that whenever they are present, they consistently produce the outcome. The results of the analysis of sufficient conditions are reported in Tables 4 and 5. The tables display the results of the intermediate solution, in which only some of the possible causal configurations not reflected by actual cases are considered to lead to the outcome. These solutions meet the minimum overall consistency and coverage criteria suggested in the literature for sufficient conditions (0.60 for coverage and 0.75 for consistency) (Schneider and Wagemann, 2010).

The results indicate three configurations. The first configuration (consistency level: 0.905) reveals that in 31.9 % of cases, high evaluations of KPI sets for circularity assessment are achieved through the application of AI and the involvement of academic researchers in adapting and contextualizing the KPIs. In this configuration, it appears that the use of AI, combined with the expertise of academic researchers, can effectively substitute for the internal R&D function, providing a comprehensive understanding of business complexities through collaboration with research experts utilizing AI.

The second configuration (consistency level: 0.93) indicates that in 32.8 % of cases, high evaluations of KPI sets for circularity assessment are achieved through cross-functional collaboration within the company, the use of AI, and the involvement of researchers, without the participation of R&D managers.

The third configuration (consistency level: 0.95) shows that in 16.7

Table 3
Necessary conditions for both achieving a high expert evaluation of the circular KPI set (Evaluation) and for its absence (∼Evaluation).

Condition	Evaluation		∼ Evaluation	
	Consistency	Coverage	Consistency	Coverage
Collaboration	0.758	0.537	0.854	0.462
∼ Collaboration	0.241	0.685	0.145	0.315
ReDinvolvement	0.358	0.406	0.685	0.594
∼ ReDinvolvement	0.641	0.728	0.314	0.272
AI	0.728	0.688	0.431	0.311
∼ AI	0.271	0.385	0.568	0.615
External	0.328	0.930	0.032	0.070
∼ External	0.671	0.476	0.967	0.523
Research	0.837	0.593	0.750	0.406
∼ Research	0.162	0.460	0.249	0.540

Notes: For each causal condition the table reports consistency and coverage values relative to the outcome (Evaluation) and to its negation (∼Evaluation). None of the conditions reaches the recommended thresholds, indicating that there are no individually necessary factors for either outcome.

Table 4
Analysis of sufficient conditions leading to a high expert evaluation of circular KPI sets.

Configurations		Raw coverage	Unique coverage	Consistency
1	~ReDinvolvement*AI*~External*Research	0.319	0.151	0.905
2	Collaboration*~ReDinvolvement*AI*Research	0.328	0.160	0.93
3	Collaboration*ReDinvolvement*~AI*External*Research	0.167	0.167	0.95

Solution coverage: 0.647.
Solution consistency: 0.917.
Frequency cutoff: 1.
Consistency cutoff: 0.86.
Notes: The table shows the configurations identifying the combinations of social-technical conditions that are sufficient to obtain a high expert evaluation of the circular KPI sets. The table reports: (i) Raw coverage: share of high-performing cases explained; (ii) Unique coverage: share explained exclusively by that configuration; and (iii) Consistency: reliability with which the configuration leads to the outcome.

Table 5
Configurations of fsQCA parsimonious solution and intermediate solution leading to a high expert evaluation of circular KPI sets.

Conditions	Configuration 1	Configuration 2	Configuration 3
Collaboration		●	●
ReDinvolvement	⊗	⊗	●
AI	●	●	⊗
External	⊗		□
Research	□	□	□

Notes: Filled symbols indicate the presence of a condition and blank spaces indicates “don’t care”.

In detail, □ indicates the presence of a core condition; ● indicates the presence of a peripheral condition; ⊗ indicates the absence of a peripheral condition.

% of cases, high evaluations are driven by cross-functional collaboration within the company, active involvement of the R&D function, and engagement with both external stakeholders and academic researchers, without reliance on AI. This configuration suggests that the company, leveraging its internal resources (internal collaboration and R&D) and cooperating with external partners and academic researchers, can develop high-quality KPIs without the need for AI.

The results obtained are closely aligned with existing research on the role of AI in the strategic support and development of KPI analysis within organizations. For example, our findings, specifically related to circularity measurement processes, fit well within the work of Zeng and Ge (2024), who argue that advanced AI frameworks enable more precise KPIs prediction by effectively modeling complex industrial processes. This aligns closely with the first two configurations, where the integration of AI and academic expertise either substitutes or complements traditional R&D functions, thereby streamlining the KPI creation process.

The third configuration emphasizes the importance of internal collaboration and external partnerships in achieving high-quality KPI development without reliance on AI. This aligns with various non-empirical studies (Burger et al., 2023), who underline that while AI tools are powerful, they must be integrated with human expertise to enhance research and management outcomes. It also correlates with empirical research, such as Caruso et al. (2023), who argue that combining traditional expertise with structured monitoring processes can mitigate challenges like “KPI overload”, ensuring effective management practices in complex organizational settings. The results of the three fsQCA configurations fit coherently within the existing literature on the role of AI and contribute to a broader understanding of how innovative approaches and collaborative frameworks can be leveraged to address the challenges of KPI development in complex and dynamic industrial contexts.

5. Discussion

The findings from the analysis conducted using fsQCA were interpreted during a workshop involving the same experts who participated in the KPI set evaluation phase to better understand the fsQCA results.

Among the key insights that emerged, it was noted that the KPI sets primarily proposed by AI consist mostly of quantitative indicators (e.g., ratios between dimensions) that are highly detailed in measuring certain aspects of corporate circularity. However, in some cases, these indicators are incredibly complex to collect. During the panel discussion with experts, it was highlighted that certain KPI sets generated with the help of AI include indicators such as the “reduction of CO_2 emissions per unit of product,” which are highly useful but fundamentally difficult to implement across all types of companies, as this would require a pre-existing data structure. As mentioned in previous studies, companies face significant challenges in calculating their carbon footprint, particularly concerning the input needed to accurately track emissions from cradle to grave—a problem especially perceived by small and medium-sized enterprises (Schmidt, 2009). In this case, it becomes evident that when AI’s technical capabilities are not synchronized with the organization’s data infrastructure and strategic priorities, it might suggest KPIs that are difficult to contextualize within the company's specific environment. On one hand, this highlights the importance of the interdependence between the organization and the AI technology implemented, emphasizing that AI tools must be fully integrated into the organization's workflows (Makarius et al., 2020). On the other hand, it is the responsibility of the manager or their support team to align these KPI sets with the company's boundaries, removing or adapting those that would require excessive effort to implement. Although AI tools may provide complex indicators that are difficult to measure and collect data for, this can certainly be seen as a catalyst for fostering a data-driven culture within companies. As highlighted in the literature, a data-oriented culture can improve business performance, also enhancing R&D activities by leveraging detailed information from collected data to drive product and process innovation (Chaudhuri et al., 2024).

In contrast, in some non-AI-generated KPI sets, experts noted the use of various qualitative-quantitative measurement scales to reduce data collection complexity and complete the indicator. For example, some indicators, though expressed as percentage ratios between dimensions, were measured using scales such as 0–25 %, 26–50 %, 51–75 %, and 76–100 %. While this approach makes the indicator easier to complete, it is less effective in highlighting improvements or deteriorations over time and provides limited guidance for developing strategies. This, in turn, restricts the company's ability to define precise circular economy strategies. In this context, AI can become a tool capable of identifying areas within business processes where data is lacking and suggesting methods for collecting the necessary information (Haefner et al., 2021).

Another aspect that emerged during the workshop with experts concerns the fact that, in some sets of KPIs developed by managers supported by researchers and AI, indicators related to more innovative industry practices were included. In contrast, in KPI sets developed without AI, the indicators are primarily based on the direct experience of managers and their knowledge of sectoral best practices. For example, in the set of KPIs developed for the construction materials industry, indicators were identified related to low-clinker cement, self-compacting concretes, and products for CO_2 capture and sequestration. From an STS perspective, this suggests that socio-technical-environmental interaction can actively contribute to organizational learning by providing access to global knowledge and emerging practices. Consequently, such interaction facilitates innovation-oriented decision-making, encouraging organizations to explore new products and processes aligned with circular economy goals. This aspect is largely in line with numerous studies that emphasize how AI may compel management to rethink a company's entire innovation process (Brynjolfsson et al., 2019; Haefner et al., 2021).

Some specific aspects and comments also emerged regarding the set of KPIs generated solely by AI. One concern relates to the difficulty AI faces in navigating the complexity of current regulations on sustainability and the circular economy, a challenge observed in other contexts as well (Morison and Harkens, 2019). For instance, it was observed that within the KPI set generated exclusively by AI, the system may suggest indicators that are already mandated by regulatory requirements. In such cases, an indicator like "providing information on the correct disposal of packaging to end users" becomes redundant in contexts where this obligation is already established by law (Amir Kavei and Savoldi, 2021). This redundancy highlights the necessity for managers to oversee and mediate between technical AI outputs and regulatory frameworks, thus in line with the STS theory (Walker et al., 2008).

Another aspect emerging from the discussion of the KPI set generated solely by AI is that some of these KPIs require further detailing and adaptation. For example, although the indicator concerning the "percentage of raw materials purchased from local suppliers" proposed in certain KPI sets aligns with the principles of the circular economy (Corsini et al., 2024) it is necessary to define the concept of "local" in terms of distance that might also be specific to the company and its sector (Bai et al., 2024). In this case, the KPI suggestion provided by the AI tool is incredibly generic, indicating that such tool lacks the ability to specify essential details, remarks the collaboration between technical systems and social systems is crucial to ensuring the indicators' strategic and operational relevance.

The last aspect that emerges from the workshop concerning KPI sets developed with and without AI support is the primary focus on descriptive or prescriptive KPIs, which are capable of monitoring a company's past performance and potentially identifying areas for improvement (Kiron et al., 2024), for example, based on past performance and sectoral benchmarks (e.g., average product lifespan). While these KPIs are essential for understanding a company's strengths and weaknesses in terms of circularity and for initiating a systematic approach to measuring circularity performance, predictive KPIs should also be integrated into a continuous improvement process (Kiron et al., 2024). Predictive KPIs can anticipate future circularity performance and foresee emerging risks, such as potential difficulties in sourcing specific materials (Di Maio et al., 2017). In this context, it appears that an even deeper level of integration is required between technological, social, and environmental components to ensure, for example, the active participation of all departments in defining data requirements, establishing standards for data collection and quality assurance, and fostering strong trust and knowledge among external collaborators. Such a profound level of integration may not have been achievable through the relatively simple KPI definition projects that form the basis of this study.

5.1. *Formulating a framework for measuring circularity with AI tools*

Building on the fsQCA results (specifically on Configuration 2, which displays the greatest explanatory strength in terms of raw coverage and unique coverage) and on the qualitative insights gathered during the expert workshop, we advance a framework for deploying AI in the measurement of corporate circularity. The configuration points to a socio-technical-environmental nexus in which managerial collaboration (social dimension), AI-enabled analytics (technological dimension), and inputs from academic and other external actors (environmental dimension) jointly underpin superior performance. Consistent with the STS principle of joint optimization (Appelbaum, 1997), AI is therefore conceived not as an isolated technical upgrade but as part of a dynamic human–machine partnership that continually adapts to organizational needs. The resulting framework is presented in Table 6.

The framework that has been formulated is grounded in the fact that enterprises are still reluctant to share data with AI (Jussen et al., 2024), given that for many business models, it is not yet clear if or how this data will be used for model training. In this context, AI is utilized solely as a tool for creating indicators, rather than for data collection, management, and processing. However, in companies where it is possible to implement and customize open-source LLM models (Ahmed et al., 2024) or federated learning models (Li et al., 2020)—where AI is trained directly on local devices without transferring or centralizing data on a single server—AI could be seen as a tool not only for generating KPIs but for managing the entire data cycle. This also highlights a key difference between large and small enterprises in the context of circularity measurement and data management in general. While small businesses must rely on commercial models that allow low-cost access to AI tools, larger companies have the capacity to develop their own models, turning them into systems capable of managing and assisting the entire measurement process till the realization of reports.

Although the framework we propose highlights the potential of AI to support the creation and refinement of KPIs for measuring circularity, it is crucial to acknowledge that ethical and practical concerns arise at each stage of the process. For instance, during the preliminary generation of KPIs through AI, inherent biases in AI training can produce skewed results that influence business decisions (Wei et al., 2025). These biases may lead to the suggestion of KPIs that do not fully capture the company's specific context or sustainability priorities, or that place disproportionate emphasis on certain types of KPIs. This underscores the

Table 6
A framework for measuring circularity with AI tools.

Stage	1. Definition of circularity objectives	2. Preliminary generation of KPIs through AI	3. Evaluation and contextualization of KPIs	4. Validation of KPIs	5. Implementation of KPIs	6. Continuous improvement
Management role (Socio)	Cross-functional team defines circular-economy objectives and ensures that AI capabilities align with corporate strategy.	Supervision and process guidance.	Management reviews the proposed KPIs and assesses their relevance and adaptability to the company context.	Cross-functional panel lead a validation to keep KPIs aligned with wider corporate goals.	Application and measurement of KPIs within the company, with the development of support procedures for data collection (avoiding 'AI-in-a-silo')	Cross-functional steering group review KPIs based on the results obtained and changes in the external context to respond dynamically to changes and uncertainties.
Role of AI (Technology)	AI can contribute by providing global trends and general suggestions on circularity.	Generate a preliminary list of KPIs, balanced against managerial guidance on firm-specific needs.	Supports in fine-tuning KPIs (e.g., new formulations)	Assists in validating and refining KPIs, identifying which KPIs are most critical for achieving circularity.	Supports the creation of data collection procedures.	Provides insights on potential scenario simulations. Develops KPI that link environmental sustainability with other business objectives, such as profitability and productivity.
Role of External Actors (e.g. research-Environment)	Support in identifying future trends and reference frameworks for measuring circularity.	Customization of open LLMs; Methodological approach for the creation of KPIs.	Support in adapting KPIs to the specific business context (e.g. comparability) and relevant frameworks.	Scientific validation of KPIs.	Methodological support for data collection.	Support in identifying future trends and reference frameworks for measuring circularity. Support in developing predictive KPI.

need for active managerial supervision and critical review (Stage 3) as outlined in our framework. The validation and implementation phases (Stages 4 and 5) also present challenges related to transparency and trustworthiness, particularly when AI is involved in data collection procedures. Data collection carried out by AI may function as a "black box" (Du Preez et al., 2024; Houser, 2019), which can limit managers' understanding of how particular values are generated and potentially weaken stakeholder trust in the measurement process. Consequently, managers must bridge the gap between algorithmic outputs and organizational realities. Furthermore, the continuous improvement and scenario simulations (Stage 6) could again suffer from AI inherent training biases, impacting managerial decisions and ultimately leading to flawed decision-making. The socio-technical interdependence described in our framework further emphasizes that AI cannot operate as a standalone instrument; rather, it requires continuous human oversight and adaptation to evolving business contexts (Makarius et al., 2020). Also in the context analyzed in our research, managers must be trained to understand both the limitations and capabilities of AI, fostering a collaborative environment in which AI augments human judgment.

5.2. Theoretical implications

The research contributes to the expansion of STS theory by providing empirical evidence of how AI tools can be effectively integrated into businesses for measuring circularity. The configuration analysis indicates that the effectiveness of the AI tool is closely dependent on active social system involvement, which must be capable of interpreting and adapting the AI-generated outputs. This finding aligns precisely with the principle of joint optimization (Appelbaum, 1997; Trist, 1981). This perspective supports previous contributions emphasizing the critical role of human-AI collaboration in addressing complex design and decision-making tasks, highlighting the necessity of human intermediaries to harness AI capabilities effectively (Bendoly et al., 2024).

The paper contributes to the theory by incorporating the role of the organizational environment, which represents a third system alongside the social and technical dimensions (Kull et al., 2013). In particular, it is interesting to observe how the often complex issue of measuring circularity can be effectively addressed by a company that commissions the development of KPIs, drawing on the support and expertise of researchers (configuration 1). This finding contributes to STS theory by demonstrating that certain functions (such as R&D) and cross-functional collaborations in specific areas can be effectively replaced by an external social system while still achieving a good level of performance. In this context, the role of these external entities is to provide specialized knowledge, regulatory and methodological guidance, and sector-specific frameworks.

The second configuration also contributes to STS theory by demonstrating that the presence of specific functions is less crucial than cross-functional collaboration for the effective integration of technology. In this case, collaboration between functions can facilitate a better understanding of company-specific needs and enable the adaptation of AI contributions accordingly. This finding supports Coiera's (2007) observations, suggesting that an explicit focus on cross-functional collaboration can help prevent the risk of designing technological systems that, by ignoring collaborative interactions within the company, are less suited to addressing organizational complexity.

Finally, as evidenced by the discussion of KPI sets through workshops, the integration of predictive KPIs emerges as a key area requiring advanced socio-technical alignment, as it demands sophisticated managerial competencies, continual employee training, adaptive organizational structures, and data governance (Makarius et al., 2020). From a theoretical perspective, these requirements underscore the relevance of socio-technical maturity and highlight the necessity of aligning technological innovations with organizational learning and capacity-building in a structured and continuous process.

6. Conclusions

Our research results indicate that AI can serve as a valuable tool for helping to structure robust KPI sets to measure circularity. In particular, we highlight the necessity of synergistic collaboration between managers and other potential actors, such as the research community, to interpret the complexities of the business sector and propose relevant KPI sets for measuring circularity at the corporate level. Based on these findings, the paper proposes an operational framework for measuring circularity using AI and offers a set of theoretical considerations to expand the STS theory.

Although the results are significant and contribute to advancing the knowledge of AI in this highly important field, certain limitations must be acknowledged. Firstly, the research considers a limited number of cases, even though the companies involved span a wide range of sectors, from manufacturing to services. Thus, the findings should be viewed as analytic generalizations rather than statistical ones; further large-scale studies are necessary to assess their robustness. Because our sample is well below power thresholds for regression, we deliberately refrained from under-powered parametric tests, relying instead on expert triangulation and calibration-sensitivity checks. Future quantitative replication with a larger survey or panel dataset will be essential to statistically validate and refine the pathways identified here.

Moreover, only one case involved the direct use of AI by the company without the support of researchers in the process. This is due to the difficulty of observing KPI set creation processes involving AI in companies without some degree of researcher involvement. Given this limitation, the study's results can be considered exploratory and would benefit from further research.

It is important to emphasize that as AI evolves, it could develop more advanced reasoning, analysis, and contextualization capabilities, enabling deeper and more effective integration of its functions in businesses while also reducing the need for alignment between social and technical components. For this reason, it is essential to continue progressive research on the role of AI in measurement and to prospectively understand how these dynamics may evolve, potentially leading to a significant reconceptualization of STS theory. Among future research directions, it will be crucial also to address more extensively the ethical challenges associated with AI use, particularly in the creation of KPIs. This includes issues such as the transparency of the approaches used and whether AI could become a tool that facilitates cherry-picking data and indicators, potentially leading to misleading communication.

CRediT authorship contribution statement

Filippo Corsini: Writing – review & editing, Writing – original draft, Validation, Methodology, Investigation, Formal analysis, Conceptualization. **Tiziana Iannuzzi:** Writing – review & editing, Writing – original draft, Methodology, Investigation, Formal analysis. **Marta Fundoni:** Writing – review & editing, Writing – original draft, Methodology, Investigation, Formal analysis. **Marco Frey:** Writing – review & editing, Supervision.

Declaration of competing interest

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

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jclepro.2025.146488.

Data availability

The authors do not have permission to share data.

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