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Enhancing Circular Economy Business Performance through Supply Chain Transparency: The Roles of Digital Technologies and Institutional Support

Muhammad Mansha[1], Amina Alamgir[2]

[1] Scholar, College of Economics and Management, Northwest Agricultural and Forestry University, Yangling, Shaanxi, China. Email: muhammadmansha2250@gmail.com

[2] PhD Scholar, Department of Economics, The Islamia University of Bahawalpur, Pakistan. Email: aminaalamgir786@gmail.com

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ABSTRACT

Circular economy transition is now a strategic approach in China as the country tries to balance economic development and environmental sustainability. Digital technologies and institutional support are now considered as key facilitators of this shift, but the empirical data on how these drivers can be converted into the business performance of the circular economy has been heterogenous, especially with respect to the importance of supply chain transparency and complementary operational capabilities. The paper examines the role of digital technologies, that is, Digital Platform Integration, Artificial Intelligence Adoption, Blockchain Integration Internet of Things Utilization and the impact of Institutional Support to Sustainability on Circular Economy Business Performance in China. It also investigates the mediating effect of Supply Chain Transparency, the moderating effects of Reverse Logistics Efficiency and Circular Supply Chain Performance. The research design was quantitative relying on survey data on 387 Chinese involved in supply chain, sustainability and digital transformation activities. Partial Least Squares Structural Equation Modeling (PLS-SEM) with SmartPLS was applied to the proposed conceptual framework to test both the measurement and structural models, as well as mediation and moderation effect. The findings indicate the positive impacts of all the investigated digital technologies and institutional support on the supply chain transparency are significant. On the other hand, supply chain transparency has a positive influence on the business performance of the circular economy in a strong way. In addition, the circular supply chain performance and reverse logistics efficiency enhance the positive association between supply chain transparency and the circular economy business performance significantly. The results can be used by managers and policymakers in China as it indicates that investments into digital technologies should be accompanied by open supply chain practices and effective reverse logistics systems to achieve the full benefits of the circular economy. These transformations continue to require institutional support to speed them up and maintain them. This research presents one of the limited empirical analyses of institutional support and digital technologies combined to form a circle of business performance related to a supply chain transparency in the Chinese environment and considers the main operational contingencies.

Corresponding Author's Email: muhammadmansha2250@gmail.com

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1. Introduction

The shift towards the circular economy has become a strategic necessity to economies that seek to balance industrial growth and environmental preservation. The principles of the circular economy are based on the need to make resources efficient, minimize waste, and retain value across production and consumption networks, thus becoming a radical shift in the traditional linear thinking (Geissdoerfer et al., 2017; Korhonen et al., 2018; Lieder & Rashid, 2016). In the case of manufacturing- and supply-chain-intensive economies like China, the circular economy is an environmental necessity and provides a channel to industrial upgrading, competitiveness and economic resilience in the long-term (Acerbi & Taisch, 2020; Schroeder et al., 2018; Stucki et al., 2023).

It is a well-known fact that digital transformation is the key facilitator in the process of circular economy implementation. Digital technologies enhance information flows, coordination, and monitoring in complex supply networks, which forms a fundamental requirement of the material loop closure and circular performance improvement (Kristoffersen et al., 2020; Pagoropoulos et al., 2017; Vial & G, 2021). Specifically, the incorporation of digital platforms can strengthen inter-organizational cooperation and ecosystem-level value creation by facilitating real-time data sharing between two or more stakeholders (Cennamo et al., 2020; Jacobides et al., 2018; Nambisan et al., 2019). These platforms are becoming more relevant in the digitally intensive industrial environment of China, where platform-based coordination has become a leading logic of organization.

Besides the digital platforms, emerging Industry 4.0 technologies, such as artificial intelligence, blockchain and the Internet of Things, play a significant role in driving circular supply chains. Artificial intelligence enhances both the efficiency and sustainability of operations by processing large volumes of data related to operations, thereby increasing both the efficiency and sustainability of operations (Jarrahi, 2018; Jianjun et al., 2021; Mukherjee et al., 2024; Wamba-Taguimdje et al., 2020). The technology of blockchain improves supply chain traceability, data integrity and trust that are necessary to ensure transparent circular flows and accountability (Casino et al., 2019; Saberi et al., 2018; Shrivastav & Bag, 2024). In the same manner, Internet of Things technologies enable real-time tracking and monitoring of products, materials, and processes throughout the lifecycle, which supports the activities of reverse logistics and resource recovery (Ghadge et al., 2020; Hrouga et al., 2022; Rejeb et al., 2022).

Although this promise exists on a technological level, the realization of the benefits of a circular economy depends heavily on the institutional setting in which companies' function. The institutional support of sustainability through regulatory mechanisms, policy tools and normative pressures encourages firms to implement environmentally friendly practices, as well as invest in digital technologies that are aligned with sustainability goals (Delmas & Toffel, 2004; DiMaggio & Powell, 2000; North, 1990). The sustainability initiatives, environmental policies, and digital regulating systems in China have created significant external forces and incentives that push companies to embrace circular and transparent supply chain operations (Makohon, 2021; Medaglia et al., 2024).

Empirical studies are increasingly highlighting the relevance of supply-chain transparency as a critical mediating factor that facilitates the connection between new digital technologies, institutional forces, and the achievement of a circular economy goal. Transparency will help to establish stronger monitoring of environmental and social practices across supply-chain networks by reducing information asymmetries and promoting coordination (Dou & Sarkis, 2010; Klassen & Vereecke, 2012; Zhu et al., 2012). Furthermore, transparent supply chains are especially impactful on the work of the enterprises that are focused on the circular economy since they make it possible to achieve increased efficiency in reverse logistics, resource recovery, and closed-loop operations (Genovese et al., 2017; Ravi & Shankar, 2005; Rogers & Tibben-Lembke, 1998; Sadiq et al., 2024).

Even though previous researchers have explored digital technologies, institutional aspects, and practices of the circular economy separately, there is a scarcity of empirical studies that combine these aspects into a single explanatory model, especially in the Chinese context. The current literature recommends more comprehensive models that would reflect the interplay between digital platform integration and Industry 4.0 technologies with institutional support to increase supply chain transparency and, eventually, business performance of the circular economy (Aarikka-Stenroos et al., 2021; Ranta et al., 2021; Rogers & Tibben-Lembke, 1998). To fill this gap, the current study formulates and empirically assesses an integrative framework, which examines the role of digital platform integration, adoption of artificial intelligence, blockchain integration, use of Internet of Things, and institutional facilitation of sustainability on supply chain transparency, circular supply chain performance, and the performance of businesses within the circular economy paradigm in China(Dhivya et al., 2023; Ragmoun & Ben-Salha, 2024).

By focusing on China, this work contributes to the body of knowledge on the topic of circular economy and digital transformation by placing it in the context of an emerging economy that has strong institutional power and fast technological penetration. The empirical data provides theoretical information on how digital and institutional forces can work together to drive the results in the circular economy, and also provides practical suggestions to managers and policy makers who strive to accelerate the process of creating sustainable and transparent supply chains(Chien et al., 2021; Nawab et al., 2021).

2. Theoretical Framework

The theoretical framework of the study combines the resource-based view, dynamic capabilities theory, and institutional theory to frame the connection between digital technologies and institutional forces and the circular economy business performance in China. In terms of resource-based approach, digital platforms, artificial intelligence, blockchain, and the Internet of Things are among the valuable organizational resources that contribute to the improvement of information processing, coordination, and sustainability performance (Barney, 1991; Westerman et al., 2011; Yoo et al., 2012). The dynamic capabilities theory suggests that organizations should constantly restructure their digital assets to effectively accommodate technological change and sustainability demands, which is especially acute in fast-paced industrial environments like China (Sirmon et al., 2010; Sirmon et al., 2007; Teece, 2007; Vial & G, 2021).

Inter-organizational connectivity and real-time exchange of data through the integration of digital platforms increases the visibility and coordination across supply chains (Cennamo et al., 2020; Hettithanthri & Dewapriya, 2024; Nambisan et al., 2019). Artificial intelligence enhances analytical and monitoring capabilities that are used to support transparency and decision-making in the context of circular flows (Jarrahi, 2018; Wamba-Taguimdje et al., 2020). Blockchain is used to significantly improve transparency as it ensures traceability, data integrity, and trust between supply-chain partners (Bekrar et al., 2021; Casino et al., 2019; Saberi et al., 2018) compared to the Internet of Things (IoT) that helps trace and track products and materials along with their lifecycle (Dutta et al., 2022; Ghadge et al., 2020; Rejeb et al., 2022). The institutional theory explains the processes through which the regulatory frameworks, policy incentives, and normative pressures in China encourage the incorporation of transparent and sustainability-oriented supply chain practices (Delmas & Toffel, 2004; DiMaggio & Powell, 2000; Medaglia et al., 2024; North, 1990).

In the proposed framework, supply chain transparency is characterized as a central mediating capability that allows converting digital and institutional resources into improved performance in the circular economy by alleviating information asymmetry and coordinating the activity across circular supply chains (Genovese et al., 2017; Klassen & Vereecke, 2012; Zhu et al., 2008). The effects of transparency on performance will depend upon the capabilities of firms, especially their reverse logistics and circular supply chain performance, since they will decide the extent to which transparent information is translated into circular results (Genovese et al., 2017; Klassen & Vereecke, 2012; Ravi & Shankar, 2005; Rogers & Tibben-Lembke, 1998; Zhu et al., 2008). Together, the framework explains the way in which digital transformation and institutional support contribute to transparency-based business performance of the Chinese circular economy (Ragmoun & Ben-Salha, 2024).

2.1. Hypotheses Development

Based on the resource based perspective and the dynamic capabilities perspective, digital technologies, and institutional support can be theorized through the prism of strategic assets that enable the creation of high-quality information visibility and sustainability-oriented capabilities among Chinese companies, which results in a higher quality of performance in the context of circular economy projects (Barney, 1991; Sirmon et al., 2010; Teece, 2007). The integration of digital platforms in China is a fast-digitizing industrial setting, where inter-organizational connectivity and data sharing amidst supply chain participants are reinforced through digital platforms, thus boosting end-to-end visibility and traceability, which, in turn, enhances supply chain transparency (Cennamo et al., 2020; Hettithanthri & Dewapriya, 2024; Nambisan et al., 2019; Yoo et al., 2012). Therefore, H1: Digital Platform Integration (DPI) has a positive impact on Supply Chain Transparency (SCT) in China. The application of artificial intelligence also enhances transparency by providing better analytics, decision-support, and anomaly detection that could transform large amounts of operational data into real-time data, which bolsters monitoring and disclosure in supply networks (Grover et al., 2024; Jarrahi, 2018; Mishra et al., 2024; Wamba-Taguimdje et al., 2020). Accordingly, H2: Artificial Intelligence Adoption (AI) has a positive influence on Supply Chain Transparency (SCT) in China.

It is also anticipated that by implementing blockchain, supply chain transparency will be improved due to the ability to ensure tamper-resistance, provenance, and verifiable records which could be used to increase the trust and the integrity of information within the supply chain partners (Bekrar et al., 2021; Casino et al., 2019; Saberi et al., 2018). Therefore, H3: Blockchain Integration (BCI) has a positive impact on Supply Chain Transparency (SCT) in China.

Moreover, increased transparency is achieved through the implementation of Internet of Things technologies, which helps to ensure real-time sensing, monitoring, and data collection at logistics and production nodes, thereby increasing visibility, traceability, and responsiveness in the supply chain operations (Dutta et al., 2022; Ghadge et al., 2020; Rejeb et al., 2022; Shoomal et al., 2024). In line with this, Hypothesis 4 is that the usage of the Internet of Things (IoT) has a positive impact on supply-chain transparency (SCT) in China. In addition to technological factors at the firm level, institutional sustainability in China is likely to be strengthened by transparency, which is promoted by regulatory pressures, stakeholder expectations, and the supportive policy frameworks that facilitate the disclosure and formalization of sustainability and operational information across supply chains (Celac, 2012; Delmas & Toffel, 2004; DiMaggio & Powell, 2000; Makohon, 2021; Medaglia et al., 2024; North, 1990). Thus, Hypothesis 5 provides that institutional support to sustainability (ISS) has a positive impact on the supply-chain transparency (SCT) in China.

By improving transparency, companies can reduce information asymmetries, enhance coordination, and reinforce compliance and accountability through the entire circular flows, which facilitates performance in circular economy projects (Bag et al., 2020; Genovese et al., 2017; Klassen & Vereecke, 2012; Schroeder et al., 2018; Zhu et al., 2008, 2012).

Hypothesis 6 (H6) will be that Supply Chain Transparency (SCT) positively affects Circular Economy Business Performance (CEBP) in the Chinese context. Circular operations are also moderators of the relationship between transparency and performance. The higher efficiency of the reverse logistics supports the conversion of the transparent information into effective recovery, take-back, remanufacturing, and recycling results, thus augmenting the performance advantages of transparency (Almelhem et al., 2024; Daramola et al., 2023; Khan et al., 2020). (Torgerson and Tibben-Lembke, 1998). Hypothesis H7, therefore, assumes that Reverse Logistics Efficiency (RLE) is a positive moderator between Supply Chain Transparency (SCT) and Circular Economy Business Performance (CEBP) in the Chinese context, that is, the stronger the relationship between SCT and CEBP, the greater the moderation of the relationship by RLE.

Furthermore, the improved functioning of the circular supply chain also leads to the better coordination and operational performance of the supply chain, thus continuing to increase the ability of transparency to bring performance gain (Farshadfar et al., 2024; Genovese et al., 2017; Jum'a et al., 2024; Karmaker et al., 2023; Romagnoli et al., 2023).

Therefore, H8 states that Circular Supply Chain Performance (CSCP) moderates the relationship between Supply Chain Transparency (SCT) and Circular Economy Business Performance (CEBP) in China, the moderating effect increasing with the increase of CSCP.

The theoretical framework provided below assumes that the digital platform integration, artificial intelligence adoption, blockchain technology inclusion, Internet of Things solutions implementation, and institutional support of sustainability are all crucial antecedents to sustainability-related supply chain transparency. These digital and institutional enablers promote better visibility, traceability, and flow of information among supply chains thus improving the level of transparency. Supply chain transparency, therefore, acts as a focal mediating construct that these antecedents affect business performance in the framework of the circular economy. The model also incorporates reverse logistics efficiency and circular supply chain performance as moderating variables that precondition the correlation between supply chain transparency and circular economy business performance. Particularly, it is expected that the beneficial impact of supply chain transparency on the business performance of the circular economy will be enhanced by the fact that the companies will exhibit greater reverse logistics efficiency, and a more developed state of the circular supply chain performance. Overall, the framework explains how digital technologies and institutional facilitation can be converted into the high-quality business results of the circular economy by promoting transparency, and how the operational capabilities serve as a boundary condition.

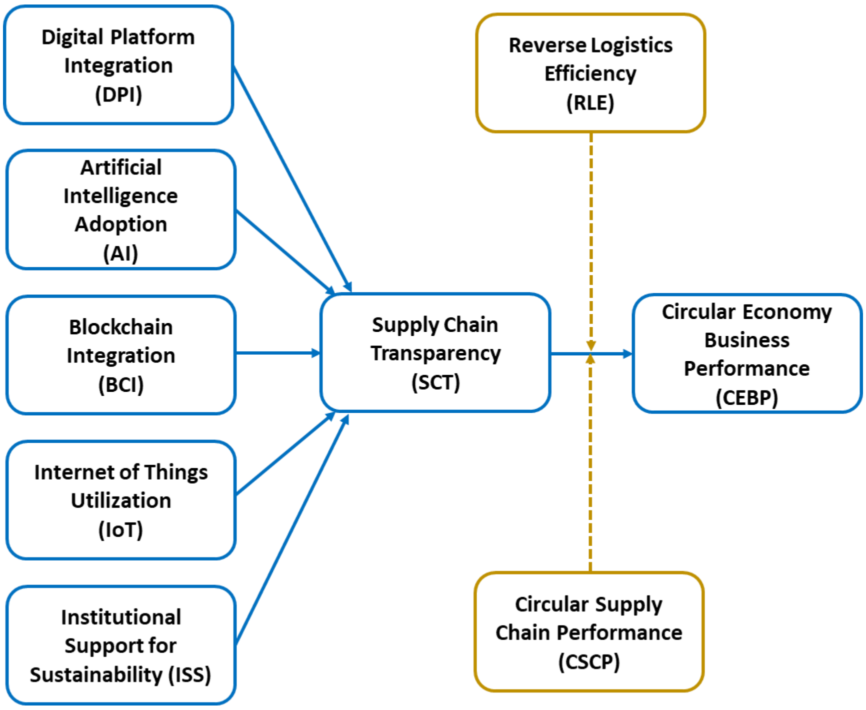

Figure 1: Conceptual Framework of the Study

3. Data and Methodology

3.1. Constructs Development

Synthesis of measurement instruments based on a collection of items derived out of various underlying studies is a well-established and highly accepted methodological approach, especially when (a) the construct being studied is complex or emergent, (b) a single theoretically sound scale is insufficient to cover the construct domain, and (c) the synthesized items are theoretically based on existing scholarly literature (Churchill, 1979; DeVellis & Thorpe, 2021; Hinkin, 1998; MacKenzie et al., 2011).

However, the instruments constructed in this way should be strictly justified by transparent documentation of the item generation, screening, and refinement processes; guaranteeing content validity by using expert reviews, pretesting; and thoroughly statistically validated in terms of internal consistency, convergent validity, and discriminant validity, multicollinearity, and structural consistency with theoretical assumptions (Churchill, 1979; DeVellis & Thorpe, 2021; Fornell & Larcker, 1981; Hinkin, 1998).

3.2. Measurement Development and Validation

Measurement scales used in this paper were developed based on the existing recommendations on construct and scale development in the sphere of management and sustainability research (Churchill, 1979; DeVellis & Thorpe, 2021; Hinkin, 1998; MacKenzie et al., 2011). This methodological process is especially applicable to exploring complex and emerging phenomena, including knowledge-based eco-innovation and circular supply chains, in which no single validated measure can adequately cover the construct domain.

1. First, domain specification was done through clearly defining the conceptual limit of each construct using foundational theories and previous empirical studies related to knowledge management, eco-innovation, circular economy and environmental performance (Churchill, 1979; Hinkin, 1998; MacKenzie et al., 2011). This measure brought about conceptual clarity and the differentiation between every construct and other related but theoretically different concepts.
2. Second, the development of measurement items was done by conducting a thorough review of the existing literature. They were not directly borrowed out of a single study but synthesized based on several underlying and commonly used studies, thus allowing a full measure of the multidimensional and contextualized nature of the constructs (Churchill, 1979; DeVellis & Thorpe, 2021; Hinkin, 1998). All the items were phrased in a reflective manner and were in line with the theoretical definitions of the respective construct.
3. Third, expert review was used to guarantee content validity. The first pool of items was tested by subject-matter experts holding knowledge in the areas of sustainability, innovation management, and supply chain research and tested the item clarity, relevance, and representativeness. Based on the expert review feedback, some small wording changes were made to improve clarity and the situational appropriateness (DeVellis & Thorpe, 2021; Hinkin, 1998; MacKenzie et al., 2011).
4. Fourth, a pilot study was done using a small sample that was representative of the target population before full data collection commenced. The pilot study has helped discover possible ambiguities in the phrasing and has allowed the researcher to ensure consistent interpretation of the items by the respondents, thus resulting in additional minor revisions that have improved the overall quality and readability of the questionnaire (DeVellis & Thorpe, 2021; Hinkin, 1998).
5. Lastly, the statistical validation was obtained by using the Partial Least Squares Structural Equation Modeling (PLS-SEM) with the help of the SmartPLS, which was applied in compliance with the methodological principles outlined by (Hair et al., 2019). Internal consistency reliability was assessed using Cronbachs alpha and composite reliability scores with each of them exceeding the traditional value of 0.70, as suggested by Nunnally (1994) and restated by Hair et al. (2019). Outer loadings of more than 0.70, and average variance extracted (AVE) of above 0.50, supported convergent validity, which met the standards suggested by Fornell and Larcker (1981) and were supported by Hair et al. (2019). The Fornell-Larcker criterion, the heterotrait-monotrait ratio, and the cross-loading analysis were used to determine discriminant validity and met the recommended thresholds (Fornell & Larcker, 1981; Henseler et al., 2014). Multicollinearity was evaluated through the variance-inflation factors (VIF), and they did not exceed the critical values, thus, the presence of collinearity issues was eliminated (Hair et al., 2019; Kock, 2015). Taken together, the results present strong measurements of reliability, convergent validity, discriminant validity, and correspondence to the expected theoretical framework, thus validating the appropriateness of the developed measurement scales to the further analysis of structural models (Hair et al., 2019; MacKenzie et al., 2011).

3.3. Data Collection and Sample

This study used empirical data that were gathered through a structured questionnaire given to the potential respondents in China. China is an appropriate empirical setting due to the rapid digitalization, strong institutional participation in sustainability efforts, and proactive support of the practices of a circular economy within its industrial sectors. The respondents that were targeted included managers, professionals, and decision-makers who had a direct connection to digital transformation, supply-chain management, sustainability efforts, or activities related to circular-economy in their respective organizations. The number of valid responses was 387 which was retained to be analyzed finally.

This is a larger sample size than the minimum required in Partial Least Squares Structural Equation Modeling (PLS -SEM) and it has enough statistical power to estimate complex models that involve multiple constructs and interacting effects (Green, 1991; Hair et al., 2019). The method of data collection was a self-administered survey, which guaranteed the anonymity of respondents and the maintenance of confidentiality, which helps reduce evaluation apprehension and increase the truthfulness of the answers (Podsakoff et al., 2024).

3.4. Measurement Instrument

Each of the constructs was operationalized in terms of multi-item reflective scales, which were designed and tested in accordance with the general procedures of scale development and validation, as outlined in the previous subsection. The respondents were asked to specify the degree of their agreement with every statement on a Likert-type scale. A pilot test was conducted to determine the clarity and relevance of the questionnaire to the context and consistent interpretation of items before the actual administration of the questionnaire (DeVellis & Thorpe, 2021; Hinkin, 1998).

3.5. Analytical Technique

The analysis was done by using SmartPLS to analyze data through Partial Least Squares Structural Equation Modeling (PLS-SEM). The use of PLS-SEM is especially effective in this study because it can deal with complex models, interaction effects and prediction-based goals. It is also strong when the data distribution is non-normal (Hair et al., 2017; Hair et al., 2019). The approach is highly suggested in sustainability, innovation and supply chain studies where theory building, and model extension become the main goals.

The analysis was done using a two-step process. The measurement model was tested in the first stage to determine the internal consistency reliability, convergent validity, discriminant validity, and the lack of multicollinearity as per the recommended methodology (Fornell & Larcker, 1981; Hair et al., 2019; Kock, 2015).

The second stage involved the evaluation of the structural model by analyzing path coefficients, t-statistic and p-values through a bootstrapping process to test the hypothesized relationships and interaction effects (Hair et al., 2019).

3.6. Common Method Bias

Since the data were gathered in one source, and the study design was cross-sectional survey, common method bias was considered. Full collinearity variance inflation factors (VIFs) were analyzed in line with the recommended procedures, and all values were lower than the critical thresholds, which means that common method bias was not a significant issue in this study (Kock, 2015; Podsakoff et al., 2024). In general, the chosen data collection mechanisms and the analysis plan represent a strict methodological basis to test the suggested interconnections between digital technologies, institutional support, supply chain transparency and the performance of the Chinese circular economy.

4. Results

The results of the convergent validity test of all constructs in the measurement model i.e. Artificial Intelligence Adoption, Blockchain Integration, Circular Economy Business Performance, Circular Supply Chain Performance, Digital Platform Integration, Institutional Support for Sustainability, Internet of Things Utilization, Reverse Logistics Efficiency, and Supply Chain Transparency are shown in Table 1.

Table 1
Convergent Validity Test

Constructs	Items	Loading	Alpha	CR	AVE
AI	AI1	0.803	0.869	0.871	0.657
	AI2	0.818			
	AI3	0.82			
	AI4	0.793			
	AI5	0.818			
BCI	BCI1	0.784	0.886	0.887	0.636
	BCI2	0.788			
	BCI3	0.815			
	BCI4	0.817			
	BCI5	0.8			
	BCI6	0.782			
CEBP	CEBP1	0.8	0.867	0.869	0.653
	CEBP2	0.827			
	CEBP3	0.796			
	CEBP4	0.822			
	CEBP5	0.794			
CSCP	CSCP1	0.798	0.885	0.893	0.633
	CSCP2	0.814			
	CSCP3	0.788			
	CSCP4	0.8			
	CSCP5	0.788			
	CSCP6	0.786			
DPI	DPI1	0.817	0.871	0.877	0.659
	DPI2	0.805			
	DPI3	0.802			
	DPI4	0.841			
	DPI5	0.792			
ISS	ISS1	0.793	0.881	0.883	0.628
	ISS2	0.792			
	ISS3	0.792			
	ISS4	0.784			
	ISS5	0.796			
	ISS6	0.796			
IoT	IoT1	0.83	0.837	0.838	0.672
	IoT2	0.817			
	IoT3	0.824			
	IoT4	0.807			
RLE	RLE1	0.817	0.869	0.87	0.656
	RLE2	0.801			
	RLE3	0.816			
	RLE4	0.798			
	RLE5	0.818			
SCT	SCT1	0.811	0.862	0.862	0.644
	SCT2	0.806			
	SCT3	0.787			
	SCT4	0.804			
	SCT5	0.804			

The assessments of convergent validity in terms of indicator loadings, Cronbach alpha, composite reliability, and average variance extracted were measured according to the existing PLS-SEM standards. All measurement items have high standardized loadings ranging between 0.782 to 0.841 which are above the traditional level of 0.70 and this implies that the indicators are appropriate to reflect their respective constructs and no deletion of items is necessary. The internal consistency is also good with Cronbach alpha values between 0.837 and 0.886 and composite reliability levels between 0.838 and 0.893, all well above the minimum acceptable level of 0.70. Additionally, the average variance that each construct extract is between 0.628 and 0.672 which is considerably higher than the cutoff of 0.50 and thus indicates that each construct explains more than 50 percent of the variance in its indicators. These findings, put together, indicate that the measurement model has sufficient reliability and high convergent validity.

Table 2 shows the HTMT ratios that were used to assess discriminant validity of the constructs. All the HTMT values are much lower than the traditional standard of 0.85, with the highest ratio value between Supply Chain Transparency and Circular Economy Business Performance (0.731), which is still acceptable. Most of the values of HTMT are significantly less, which in turn implies there is a distinct difference between the constructs and little overlap in the concept. The inferences of these findings are that each of the constructs captures a specific aspect of the theoretical construct and is empirically distinctable of the other. In general, the HTMT analysis supports the fact that the measurement model has achieved satisfactorily the test of discriminant validity which in turn allows the study to proceed with the evaluation of the structural model.

Table 2
HTMT Ratio

	AI	BCI	CEBP	CSCP	DPI	ISS	IoT	RLE	SCT
AI									
BCI	0.279								
CEBP	0.368	0.416							
CSCP	0.307	0.253	0.368						
DPI	0.276	0.235	0.394	0.326					
ISS	0.254	0.316	0.382	0.186	0.183				
IoT	0.195	0.313	0.318	0.251	0.14	0.238			
RLE	0.192	0.245	0.336	0.239	0.191	0.258	0.135		
SCT	0.496	0.582	0.731	0.391	0.504	0.536	0.431	0.258	

The findings of Fornell-Larcker criterion which is used to test the discriminant validity are shown in Table 3. The square roots of the AVE values as represented on the diagonal are greater compared to the relative inter-construct correlations in the same rows and columns among all the constructs. This trend shows that the construct has a higher percentage of variance in common with its constituent indicators compared with the indicators in other constructs in the model. The pairwise correlations of the different constructs have also been found to be relatively low and this again supports the claim that the constructs are empirically distinct and represent distinct theoretical concepts. Overall, the FornellLarcker analysis provides sufficient support to the presence of sufficient discriminant validity, which strengthens the validity of the measurement model and allows proceeding with the assessment of the structural model.

Table 3
Fornell-Larcker

	AI	BCI	CEBP	CSCP	DPI	ISS	IoT	RLE	SCT
AI	0.81								
BCI	0.246	0.798							
CEBP	0.319	0.364	0.808						
CSCP	0.269	0.226	0.33	0.796					
DPI	0.246	0.205	0.346	0.29	0.812				
ISS	0.222	0.282	0.334	0.17	0.161	0.792			
IoT	0.166	0.272	0.272	0.215	0.121	0.203	0.82		
RLE	0.169	0.216	0.294	0.213	0.167	0.228	0.116	0.81	
SCT	0.431	0.51	0.633	0.348	0.441	0.469	0.367	0.224	0.803

Table 4 shows the cross-loadings of all measurement items and each of the indicators has the highest loading on its specific construct compared with other constructs in the model. The loading on the corresponding constructs is always strong; they are usually over 0.78; the cross-loading onto non-target constructs is significantly low, thus, indicating a minimal overlap of constructs. As an example, objects related to AI, BCI, CEBP, CSCP, DPI, ISS, IoT, RLE, and SCT all have the highest values on their respective latent variables, and there are no problematic cross-loadings close to or exceeding the primary ones. The trend proves that the constructs represent unique concepts and indicators are not unnecessarily affected by other constructs within the model. In general, the findings of the cross-loading give additional evidence of sufficient discriminant validity and the strength of the measurement model.

4.1. Measurement Model

Figure 2 shows the measurement model and shows that all the constructs are measured in a good and appropriate way. The indicators show high outer loadings on the respective latent variable with most of the values significantly higher than the recommended level of 0.70, which implies that the items are the strong representatives of the intended constructs. The constructs: Digital Platform Integration, Artificial Intelligence Adoption, Blockchain Integration, Internet of Things Utilization, Institutional Support of Sustainability, Supply Chain Transparency, Reverse Logistics Efficiency, Circular Supply Chain Performance, and Circular Economy Business Performance are operationalized by various indicators each with a consistent and significant load on its respective latent factor. The lack of weak or problematic loading implies that no indicator elimination is obligatory. Overall, the figure confirms the sufficiency of the measurement model in the context of indicator reliability and justifies the use of these constructs in further structural model analysis.

Table 4
Cross Loadings

	AI	BCI	CEBP	CSCP	DPI	ISS	IoT	RLE	SCT
AI1	**0.803**	0.217	0.265	0.273	0.227	0.158	0.138	0.13	0.336
AI2	**0.818**	0.200	0.276	0.204	0.214	0.194	0.095	0.13	0.378
AI3	**0.820**	0.191	0.244	0.205	0.172	0.154	0.16	0.161	0.349
AI4	**0.793**	0.182	0.260	0.191	0.166	0.198	0.132	0.13	0.32
AI5	**0.818**	0.205	0.245	0.220	0.214	0.197	0.15	0.133	0.36
BCI1	0.148	**0.784**	0.278	0.166	0.167	0.182	0.211	0.158	0.382
BCI2	0.215	**0.788**	0.369	0.165	0.193	0.193	0.216	0.186	0.402
BCI3	0.190	**0.815**	0.280	0.210	0.172	0.245	0.198	0.164	0.429
BCI4	0.257	**0.817**	0.261	0.178	0.154	0.200	0.209	0.173	0.42
BCI5	0.170	**0.800**	0.287	0.168	0.144	0.330	0.258	0.184	0.423
BCI6	0.194	**0.782**	0.272	0.193	0.152	0.192	0.207	0.166	0.38
CEBP1	0.241	0.265	**0.800**	0.260	0.261	0.244	0.186	0.242	0.513
CEBP2	0.187	0.312	**0.827**	0.308	0.302	0.273	0.22	0.277	0.533
CEBP3	0.264	0.291	**0.796**	0.233	0.213	0.272	0.291	0.202	0.469
CEBP4	0.309	0.321	**0.822**	0.267	0.291	0.285	0.218	0.2	0.526
CEBP5	0.291	0.283	**0.794**	0.262	0.324	0.274	0.19	0.26	0.511
CSCP1	0.222	0.190	0.288	**0.798**	0.237	0.131	0.131	0.187	0.306
CSCP2	0.201	0.187	0.314	**0.814**	0.251	0.210	0.188	0.191	0.326
CSCP3	0.199	0.158	0.196	**0.788**	0.219	0.094	0.187	0.139	0.229
CSCP4	0.237	0.180	0.262	**0.800**	0.252	0.095	0.168	0.142	0.267
CSCP5	0.211	0.194	0.235	**0.788**	0.209	0.150	0.171	0.16	0.258
CSCP6	0.215	0.164	0.252	**0.786**	0.205	0.109	0.19	0.183	0.249
DPI1	0.209	0.185	0.276	0.271	**0.817**	0.148	0.109	0.178	0.363
DPI2	0.211	0.125	0.298	0.248	**0.805**	0.125	0.08	0.138	0.37
DPI3	0.139	0.160	0.260	0.194	**0.802**	0.123	0.089	0.103	0.303
DPI4	0.251	0.161	0.313	0.233	**0.841**	0.159	0.103	0.131	0.41
DPI5	0.170	0.206	0.248	0.223	**0.792**	0.091	0.109	0.122	0.327
ISS1	0.155	0.196	0.243	0.144	0.106	**0.793**	0.125	0.185	0.374
ISS2	0.186	0.197	0.299	0.170	0.164	**0.792**	0.171	0.188	0.399
ISS3	0.208	0.181	0.275	0.112	0.168	**0.792**	0.164	0.181	0.327
ISS4	0.165	0.296	0.275	0.152	0.091	**0.784**	0.19	0.218	0.38
ISS5	0.153	0.209	0.261	0.114	0.127	**0.796**	0.16	0.151	0.366
ISS6	0.192	0.256	0.233	0.112	0.113	**0.796**	0.154	0.16	0.374
IoT1	0.154	0.235	0.196	0.159	0.107	0.16	**0.83**	0.122	0.294
IoT2	0.138	0.28	0.283	0.183	0.107	0.122	**0.817**	0.085	0.319
IoT3	0.125	0.181	0.179	0.163	0.062	0.207	**0.824**	0.069	0.284
IoT4	0.126	0.188	0.225	0.198	0.117	0.18	**0.807**	0.103	0.302
RLE1	0.157	0.207	0.242	0.146	0.187	0.197	0.112	**0.817**	0.178
RLE2	0.168	0.163	0.258	0.175	0.103	0.212	0.082	**0.801**	0.205
RLE3	0.118	0.147	0.22	0.131	0.154	0.167	0.054	**0.816**	0.161
RLE4	0.104	0.146	0.232	0.135	0.075	0.182	0.086	**0.798**	0.176
RLE5	0.13	0.209	0.233	0.272	0.158	0.161	0.132	**0.818**	0.186
SCT1	0.364	0.43	0.516	0.316	0.356	0.37	0.29	0.145	**0.811**
SCT2	0.393	0.445	0.5	0.317	0.367	0.356	0.317	0.182	**0.806**
SCT3	0.327	0.387	0.494	0.225	0.35	0.374	0.321	0.16	**0.787**
SCT4	0.291	0.357	0.526	0.289	0.354	0.388	0.276	0.22	**0.804**
SCT5	0.351	0.425	0.505	0.246	0.343	0.394	0.267	0.195	**0.804**

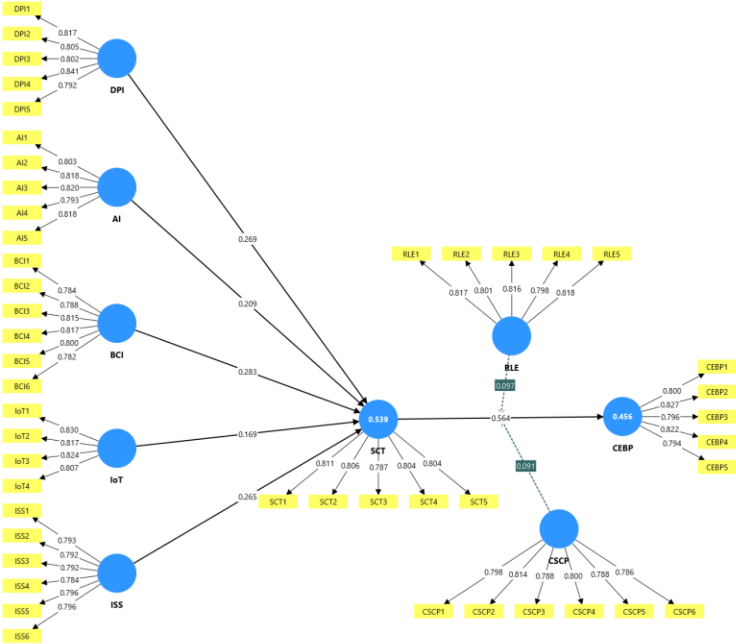

Figure 2: Measurement Model

Table 5 outlines the results of the structural path analysis and shows that all hypothesized relationships are statistically significant. Each of the Digital Platform Integration, Artificial Intelligence Adoption, Blockchain Integration, Internet of Things Utilization, and Institutional Support of Sustainability have a positive and significant impact on Supply Chain Transparency, with path coefficients ranging between 0.169 and 0.283 and a high t -value, which provides strong evidence to support hypotheses H1- H5. Among these predictors, the effects of Blockchain Integration and Digital Platform Integration have a relatively high influence on transparency, which implies the importance of digital traceability and platform connectivity. Supply Chain Transparency, in its turn, has a strong and positive impact on Circular Economy Business Performance (β = -0.564, t = 15.035), which confirms H6 and supports transparency as an influential tool that drives the results of circular performance. In addition, the interaction terms between Reverse Logistics Efficiency and Circular Supply Chain Performance and Supply Chain Transparency and Circular Economy Business Performance are positive and statistically significant, which supports H7 and H8. These findings suggest that a beneficial effect of supply chain transparency on the business performance of a circular economy is further enhanced in cases when organizations are characterized by high degrees of reverse logistics efficiency and circular supply chain performance. In general, the results provide sufficient empirical support to the developed model and confirm direct, mediated, and moderated relationships.

Table 5
Path Analysis

Hypothesis	Relation	Beta	STDEV	T statistics	P values
H1	DPI -> SCT	0.269	0.036	7.540	0.000
H2	AI -> SCT	0.209	0.035	5.967	0.000
H3	BCI -> SCT	0.283	0.037	7.683	0.000
H4	IoT -> SCT	0.169	0.036	4.761	0.000
H5	ISS -> SCT	0.265	0.037	7.096	0.000
H6	SCT -> CEBP	0.564	0.038	15.035	0.000
H7	RLE x SCT -> CEBP	0.097	0.037	2.631	0.009
H8	CSCP x SCT -> CEBP	0.091	0.034	2.648	0.008

4.2. Structural Model

The outcomes of the structural model strongly confirm the hypothesized relations. Digital Platform Integration, Artificial Intelligence Adoption, Blockchain Integration, Internet of Things Utilization and Institutional Support of Sustainability are all positively and statistically significant in Supply Chain Transparency, as indicated by high t-values, which exceed the critical value, thus confirming that digital technologies and institutional support are the key drivers of transparency. In turn, supply chain transparency has a strong and statistically significant positive impact on the performance of a circular economy business, which highlights its central mediating role in transforming technological and institutional inputs into performance outcomes. The model explains a significant amount of supply chain transparency ($R^2 = 0.539$) and circular economy business performance ($R^2 = 0.456$), which proves that it has a significant explanatory power. Further, the interaction effects reveal that Reverse Logistics Efficiency and Circular Supply Chain Performance serve as meaningful moderators and strengthen the relationship between Supply Chain Transparency and Circular Economy Business Performance. Such an observation suggests that the better-equipped firms with an effective reverse logistics system and strong circular supply chain abilities are better placed to transform transparency into high-quality circular performance.

Generally, the structural model supports the strength of the hypothesized direct, mediating, and moderating relationships, and provides a substantial empirical support of the suggested model.

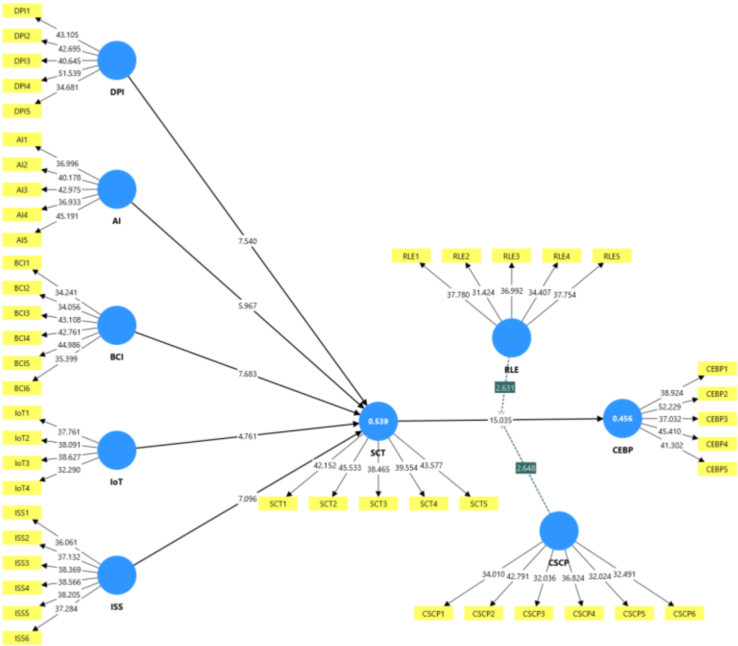

Figure 3: Structural Model

4.3. Discussion

The empirical results of this study support the main hypothesis that digitalization and institutional facilitation play a crucial role in enhancing the business outcomes of a circular economy by increasing the transparency of the supply chain in the Chinese environment.

The results of the analysis show that Digital Platform Integration, Artificial Intelligence Adoption, Blockchain Integration, Internet of Things Usage and Institutional Support of Sustainability have statistically significant positive effects on Supply Chain Transparency. This finding is consistent with the previous empirical studies that highlight the facilitative role of digital technologies in increasing transparency of information, traceability and coordination across supply chains (Ghadge et al., 2020; Kristoffersen et al., 2020; Pagoropoulos et al., 2017; Saberi et al., 2018).

According to the results of Adamashvili et al. (2024) and Dutta et al. (2022), the findings support the claim that the combination of artificial intelligence, the Internet of Things and blockchain technology can increase the flow of real-time information and records integrity, which are essential in the operations with transparency and circularity in supply chains. The existence of a strong positive relationship between the integration of digital platforms and supply chain transparency is associated with the digital ecosystem and platform-based viewpoints, according to which platforms assist in integrating across organizations, exchange data and coordinate the supply chain actors (Jacobides et al., 2018; Nambisan et al., 2019; Nemilentseva et al., 2024).

Similarly, the importance of Institutional Support of Sustainability offers empirical support to institutional theory which assumes that regulatory systems, policy incentives and stakeholder pressures contribute to transparency-focused practices and adoption of sustainability measures (Delmas & Toffel, 2004; DiMaggio & Powell, 2000; North, 1990). This observation is especially relevant to China, where the significant role of the government and policy-based sustainability efforts influence the behavior of firms and contribute to the shift to a circular economy. The findings also show that supply chain transparency has a strong and positive impact on business activities in the context of the circular economy. This finding is consistent with the prior literature that defines transparency as a central tool by which companies can improve resource efficiency, minimize waste, and recuperate value in the circular supply chains (Genovese et al., 2017; Klassen & Vereecke, 2012; Lüdeke-Freund et al., 2018).

Transparency enhances the ability of firms to operationalize circular strategies by enabling more accurate tracking of material flows and increased accountability of the process, which complements the general circular economy literature (Geissdoerfer et al., 2017; Lieder & Rashid, 2016). The theoretical contribution of the moderating role of reverse logistics efficiency and circular supply chain performance on the connection between supply chain transparency and circular economy business performance offers additional theoretical understanding. The interaction effects are positive, which means that transparency is more effective in translating into the performance outcomes in the companies that have the efficient reverse logistics systems and the developed circular supply chains capabilities. This fact correlates with the existing literature on the importance of reverse logistics and closed-loop systems in achieving the high-performance potential of the practices of the circular economy (Dabo & Hosseinian-Far, 2023; Khan et al., 2020; Rogers & Tibben-Lembke, 1998).

In addition, the results align with the resource orchestration and dynamic capabilities perspectives, which argue that resources like transparency only bring better performance when it is accompanied by an appropriate operational capability (Sirmon et al., 2010; Sirmon et al., 2007; Teece, 2007). Comprehensively, the results contribute to existing knowledge on circular economy and digital transformation by empirically showing that a combination of various digital technologies, with institutional backing, can support the overall performance of a circular economy business by increasing supply-chain transparency. Although prior studies have largely studied these technologies separately (Acerbi & Taisch, 2020; Bag et al., 2020; Kouhizadeh et al., 2022), the current study presents evidence on these technologies in China that are integrated, thus supporting recent demands to perform holistic, system-level analyses of digital-enabled circular supply chains (Ranta et al., 2021; Trevisan et al., 2023). The inclusion of these interrelationships into one empirical framework makes the research contribute to a more refined understanding of transparency as a key transmission mechanism between digital transformation and the results of the circular economy.

5. Conclusion

The present research problem is to examine the effects of a combination of digital technologies and institutional support on the outcomes of the circular economy in China, with a particular emphasis on the mediating role of supply chain transparency and the conditional impact of reverse logistics efficiency and circular supply chain performance. These findings reveal that the introduction of digital platforms, integration of artificial intelligence, integration of blockchains, use of the Internet of Things, and institutional endorsement of sustainability contribute positively to supply chain transparency, significantly improving the performance of the circular economy business. Furthermore, the positive effect of transparency on organizational performance is enhanced when companies have greater reverse logistics efficiency and more advanced circular supply chain capabilities. Altogether, the empirical evidence demonstrates that transparency serves as a key channel where digital transformation and institutional forces are converted into high-quality circular economy results and thus supports the systemic and capability-based nature of the Chinese circular transitions.

5.1. Implications of the Study

Theoretically, the work contributes to research on the circular economy and digital transformation through an empirical inclusion of a myriad of digital technologies in a single explanatory framework, thus avoiding a disaggregated analysis. The study builds on the existing studies on digitally enabled circular strategies and business-model innovation by foregrounding supply-chain transparency as a key mediating variable. The moderating role of reverse-logistics efficiency and circular supply-chain performance also adds to the insights on dynamic capability and resource orchestration by demonstrating that increased transparency provides better performance results when supported by complementary operational capabilities.

The empirical findings in the managerial setting suggest that companies that are already in China and desire to optimize the performance of the activities that are related to the circular economy should invest resources in the development of integrated digital infrastructures, including platform ecosystems, artificial intelligence, blockchain technology, and the Internet of Things. At the same time, they are supposed to develop transparency-oriented processes. It is imperative to note that the simple introduction of digital technologies does not bring the desired results unless they are supplemented by efficient reverse logistic systems and properly coordinated circular supply chains.

In the policy perspective, the crucial role of institutional support highlights the need to have consistent regulatory frameworks, incentive plans and governance strategies to accelerate the progress of transparency and the implementation of circular economy practices, particularly in policy-based environments such as China.

5.2. Limitations of the Study

Despite its contributions, this study has several limitations. To begin with, the data were gathered using the cross-sectional design, thus limiting the possibility to draw strong causal conclusions between the variables under study. Second, the study relies on self-reported survey data collected among Chinese participants, which can be vulnerable to common method bias and perceptual measurement limitations, even though the established procedural and statistical solutions have been applied. Third, the empirical setting is confined to China, which may restrain the extrapolation of the results to other institutional and economic contexts, which have different regulatory frameworks and levels of digital maturity.

5.3. Directions for Future Studies

The current investigation can be developed in several ways in the future. Longitudinal research designs may be implemented to become more successful in tracing the dynamic and evolutionary nature of digital transformation and implementing the circular economy initiatives in the course of time. Cross-country studies would help to determine whether the established associations are maintained in other emerging or developed economies that have divergent institutional structures and mechanisms of sustainability governance.

Future studies can further examine other mediating processes such as business-model innovation or knowledge integration to clarify, in more detail, the processes by which digital technologies create a circular value. Lastly, the use of qualitative or mixed-method research can provide more information on the practices and managerial decision-making mechanisms within firms that underline transparency-driven circular economy performance.

Authors Contribution
Muhammad Mansha: Conceptualization, and data analysis and complete the draft.
Amina Alamgir: Proofreading, revision and data collection.

Conflict of Interests/Disclosures
The authors declared no potential conflicts of interest regarding the article's research, authorship, and/or publication.

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Appendix

Construct	Items
Digital Platform Integration (DPI) Adapted from Casino et al. (2019); Švarc et al. (2021)	DPI1: Our organization actively uses digital platforms to manage circular business activities. DPI2: We integrate digital platforms to connect with partners across the value chain. DPI3: We use platform technologies to facilitate product reuse and recycling. DPI4: Digital platforms enhance real-time data exchange with suppliers and customers. DPI5: Our digital platform usage supports closed-loop operations.
Institutional Support for Sustainability (ISS) Adapted from Delmas and Toffel (2004); Kostka (2015)	ISS1: Our government provides incentives for circular economy initiatives. ISS2: Environmental regulations motivate our transition to circular practices. ISS3: We receive institutional support for adopting sustainable technologies. ISS4: There are policy frameworks that support green innovation in our region. ISS5: Public-private partnerships play a role in our sustainability efforts. ISS6: We receive funding or technical assistance for CE innovation.
Circular Economy Business Performance (CEBP) Adapted from: Geissdoerfer et al. (2017); Lüdeke-Freund et al. (2018)	CEBP1: Our CE practices contribute to revenue and cost efficiency. CEBP2: We have seen performance gains due to circular business models. CEBP3: Circular initiatives improved our environmental footprint. CEBP4: CE adoption has enhanced our market competitiveness. CEBP5: Our stakeholders perceive us as a circular leader.
Artificial Intelligence Adoption (AI) Adapted from: Jarrahi (2018); Wamba-Taguimdje et al. (2020)	AI1: We use AI to forecast material demands and minimize waste. AI2: Our AI tools support smart product lifecycle decisions. AI3: AI helps in identifying opportunities for circular innovation. AI4: AI is integrated into our CE decision-making processes. AI5: Our AI applications facilitate demand prediction for reused components.
Blockchain Integration (BCI) Adapted from: Casino et al. (2019); Saberi et al. (2018)	BCI1: We use blockchain to improve material traceability across the supply chain. BCI2: Blockchain enhances trust and transparency among CE stakeholders. BCI3: Our platform leverages blockchain for secure data on product histories. BCI4: Blockchain enables authentication of recovered products. BCI5: We rely on blockchain to validate reverse logistics and recycling. BCI6: Blockchain ensures secure data sharing among supply chain partners.
Internet of Things Utilization (IoT) Adapted from Ghadge et al. (2020); Zhang and Lee (2023)	IoT1: We use IoT sensors to monitor product conditions and usage. IoT2: IoT helps us track end-of-life product returns. IoT3: Our IoT systems support closed-loop material flows. IoT4: IoT-enabled tracking improves resource recovery operations.
Supply Chain Transparency (SCT) Adapted from: Dou and Sarkis (2010); Klassen and Vereecke (2012)	SCT1: We share real-time supply chain data with partners. SCT2: Our supply chain processes are visible across all stakeholders. SCT3: There is end-to-end transparency in tracking circular material flows. SCT4: Our digital systems improve supplier accountability and openness. SCT5: CE compliance across the supply chain is actively monitored.
Circular Supply Chain Performance (CSCP) Adapted from: Centobelli et al. (2020); Genovese et al. (2017)	CSCP1: Our supply chain achieves high recovery rates of used products. CSCP2: Resource efficiency has improved through CE-oriented logistics. CSCP3: Our CE operations reduce emissions and waste generation. CSCP4: We have shortened the product return and refurbishment cycle. CSCP5: Our reverse logistics are cost-effective and sustainable. CSCP6: Our supply chain meets both environmental and financial KPIs.
Reverse Logistics Efficiency (RLE) Adapted from: Ravi and Shankar (2005); Rogers and Tibben-Lembke (1998)	RLE1: We efficiently manage product returns for reuse and recycling. RLE2: Our reverse logistics are optimized with smart technologies. RLE3: Time and cost for handling returns are minimized. RLE4: Reverse flows are integrated into our forward logistics planning. RLE5: We monitor performance indicators for reverse logistics efficiency.