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Exploring Circular Digital Economy Strategies for Sustainable Environmental, Economic, and Educational Technology

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Abstract

This research explores the strategic implementation of digital economy principles to achieve environmental sustainability and economic prosperity, utilizing the SmartPLS method. In an era marked by heightened awareness of environmental challenges and the urgent need for sustainable economic solutions, the digital economy emerges as a promising and innovative approach. This study primarily focuses on the integration of digital technologies throughout the product and service life cycle, with the objectives of extending product longevity, minimizing waste, and enhancing resource efficiency. Through an extensive review of literature and multiple case studies, we delve into various dimensions of the digital circular economy. These dimensions include innovative business models, the pivotal role of consumers, the challenges encountered during implementation, and their overall impact on economic growth. The findings underscore the crucial importance of cross-sectoral collaboration and the formulation of supportive policies to unlock the full potential of this economic model. Moreover, this research highlights the synergies between digital transformation and circular economy practices, suggesting that their convergence can significantly drive sustainable progress in contemporary society. By presenting comprehensive insights into the digital economic cycle, this study aims to contribute to the discourse on sustainable innovation and provide a roadmap for policymakers, businesses, and researchers to foster a more sustainable and prosperous future.
Keywords: *SmartPLS, Education, Sustainable*

1. Introduction

In an era where environmental challenges are increasingly felt and the need for sustainable economic growth is becoming more urgent, innovation in the economic sector is crucial [1]. Emerging concepts such as the circular digital economy promise a revolutionary approach by leveraging digital technologies to achieve sustainability goals [2]. The circular economy promotes the idea that resources must be maximized, waste minimized, and product life cycles considered holistically [3]. This entails extending product life, repairing or recycling obsolete products, and ensuring that natural resources are used efficiently and sustainably. Digital technology plays a key role in facilitating this transformation, offering tools and methods to optimize resource use and reduce environmental impact [4]. The transition to a circular digital economy, however, is not without its challenges. Numerous factors need careful consideration, ranging from changes in traditional business models to consumer adaptation to more sustainable products and services [5]. Traditional linear economic models, which follow a 'take, make, dispose' approach, are deeply ingrained in many industries, making the shift to a circular model complex and multifaceted [6]. Additionally, it is essential to assess how the circular digital economy can contribute to overall economic growth while maintaining a strong focus on environmental sustainability. This dual focus requires a delicate balance between economic and ecological objectives, ensuring that neither is compromised in the pursuit of the other [7].

This study investigates the concept of a circular digital economy using the Smart Partial Least Squares (SmartPLS) method as an analytical tool [8], [9], [10]. Various aspects of the circular digital economy are explored, including evolving business models, the critical role of consumers, implementation challenges, and their impact on economic growth [11]. By employing SmartPLS, we aim to provide a robust analytical framework that can handle complex, multivariate relationships inherent in the study of circular digital economies. This method allows for the examination of both direct and indirect effects of various factors on the successful implementation of circular economy principles [12]. Cross-sector collaboration and supportive policies are vital for realizing the full potential of circular digital economy models. Strong cooperation between government, industry, academia, and civil society is essential for creating an enabling environment for sustainable innovation [13]. Government policies play a pivotal role in providing the necessary incentives for companies to adopt circular economy practices. These incentives can include tax breaks, subsidies, and grants for research and development in sustainable technologies [14]. Additionally, developing the necessary digital infrastructure, such as high-speed internet and advanced data analytics capabilities, is crucial for supporting the digital aspects of the circular economy. Public education and awareness are also key components in driving the transition to a circular digital economy [15]. Consumers play a pivotal role in driving the adoption of more sustainable products and services by making informed choices that favor environmentally friendly options. However, awareness about environmental impacts and sustainability is often not evenly distributed across all levels of society. Therefore, public outreach and education campaigns are integral to efforts aimed at changing consumer behavior towards more sustainable choices. These campaigns can take various forms, including social media initiatives, educational programs in schools, and community workshops, all designed to raise awareness about the benefits of the circular economy and the importance of sustainable living [16]. Moreover, the importance of fostering a culture of innovation and entrepreneurship cannot be overstated. Entrepreneurs and startups are often at the forefront of developing new technologies and business models that can drive the circular digital economy. Supporting these innovators through incubators, accelerators, and access to venture capital is essential for nurturing new ideas and bringing them to market. This support can help bridge the gap between concept and commercialization, ensuring that innovative solutions have the opportunity to scale and make a significant impact [17], [18].

The potential benefits of adopting a circular digital economy are immense. Not only can it significantly reduce negative environmental impacts by promoting the efficient use of resources and reducing waste, but it also offers substantial economic opportunities. The circular economy can create new jobs in areas such as recycling, remanufacturing, and digital technology development [19]. It can also enhance economic resilience by reducing dependency on finite resources and promoting more sustainable consumption patterns. Additionally, by improving the quality of life through cleaner environments and more sustainable economic practices, the circular digital economy can contribute to the overall well-being of society [20], [21], [22]. The use of advanced digital technologies, such as the Internet of Things (IoT), artificial intelligence (AI), and data analytics, has the potential to revolutionize how we produce, consume, and interact with the environment. These technologies enable the creation of smart systems that can monitor and optimize resource use in real-time, reducing waste and improving efficiency. For example, IoT devices can track the usage and condition of products, facilitating maintenance and repairs before breakdowns occur, thereby extending product lifespans. AI can analyze vast amounts of data to identify patterns and opportunities for further optimization, while data analytics can provide insights into consumer behavior and preferences, helping companies design more sustainable products and services [23], [24]. This study provides an overview of the circular digital economy concept and illustrates how this concept can be implemented in practice. By using the SmartPLS method as an analytical tool, we hope to provide valuable insights for stakeholders interested in harnessing the potential of the circular digital economy to achieve environmental and economic sustainability in the future. Through in-depth literature reviews and relevant case studies, we aim to offer a comprehensive understanding of the circular digital economy and its transformative potential. This comprehensive approach will equip practitioners, policymakers, and researchers with the knowledge and tools needed to drive sustainable innovation and foster a more sustainable and prosperous future [25], [26].

2. Literature Review

The circular digital economy represents the fusion of the traditional circular economy concept with modern digital technology, emphasizing the extension of product life, recycling of materials, and minimization of waste through technologies like the Internet of Things (IoT), artificial intelligence (AI), and data analytics. Recent studies underscore the importance of integrating these digital technologies to create a circular economy that is both economically and environmentally sustainable (Schürholz et al., 2020) [27]. Innovative business models such as subscription-based services can promote more sustainable product use by reducing the ownership of goods, encouraging manufacturers to design durable and recyclable products (Bokrantz et al., 2017) [28]. Consumers play a pivotal role by driving demand for eco-friendly products, with studies showing a preference for products with environmental certifications (Paramartha et al., 2021) [29]. Despite its potential, transitioning to a circular digital economy faces challenges such as transforming established business models and fostering stakeholder buy-in. Supportive policies, investment in digital infrastructure, and cross-sector collaboration are essential to overcoming these hurdles [30], [31].

The impact of the circular digital economy on economic growth is a subject of ongoing debate. While some studies suggest that a more sustainable economic model can drive innovation, create jobs, and enhance resource efficiency, thereby supporting long-term economic growth, empirical research is still needed to validate these claims. For instance, the Ellen MacArthur Foundation (2020) highlights the economic benefits of circular economy practices across various industries, while the European Commission (2021) provides a comprehensive review of the potential impacts on economic growth. Cross-sector collaboration and investment in digital technologies are crucial for realizing the full potential of the circular digital economy. By fostering an environment where government, industry, academia, and civil society work together, the transition to a circular digital economy can be facilitated, ultimately creating a more sustainable future. Public education and awareness campaigns are integral to changing consumer behavior towards more sustainable choices, further driving the adoption of circular practices. Through these efforts, the circular digital economy can significantly reduce environmental impacts, create economic opportunities, and improve the overall quality of life.

3. Method

3.1 Case Background

In this study, we use the Smart Partial Least Squares (SmartPLS) method as an analytical tool to investigate the concept of a circular digital economy. SmartPLS is a path analysis technique that aims to understand the relationship between variables in a structural model. This method has become a popular choice in social science and management research due to its beginnings in dealing with complex models with relatively small samples. The first step in using SmartPLS is to develop a model context that describes the relationships between variables that will be needed in the research. This model is based on relevant theory and literature in the field of circular digital economy. Variables in this model may include constructs such as digital technology adoption, consumer behavior related to well-being, the environmental impact of economic activities, and overall economic performance.

After the conceptual model is formulated, the next step is to collect the data needed to test the model. Data can be obtained through various methods, including surveys, interviews, or secondary data collection. It is important to ensure that the data collected corresponds to the variables modeled in the study and is of sufficient quality for analysis. After the data was collected, SmartPLS analysis was carried out to test the validity and significance of the relationship between variables in the model. This analysis involves various stages, including testing the reliability and validity of the measurement instrument, path analysis to test the relationship between variables, and mediation or moderation testing if necessary. The main advantage of SmartPLS is its ability to handle relatively small samples and complex models well, as well as its ability to provide parameter estimates with good accuracy even with non-normal data distributions. The results of the SmartPLS analysis provide insight into the extent to which the conceptual model can be tested empirically, as well as the strength and direction of relationships between variables. Interpretation of these results can be used to test research hypotheses and identify practical implications of the findings. In addition, SmartPLS also allows researchers to conduct comparative analysis between different groups or industries, as well as carry out sensitivity testing to changes in the models or parameters used. In the context of this paper, the use of the SmartPLS method allows us to test the conceptual model of the circular digital economy empirically, providing a deeper understanding of the factors influencing the adoption and implementation of the circular digital economy, as well as its impact on economic and environmental performance. Thus, this method becomes an invaluable tool in answering our research questions and makes a significant contribution in expanding our understanding of the circular digital economy concept.

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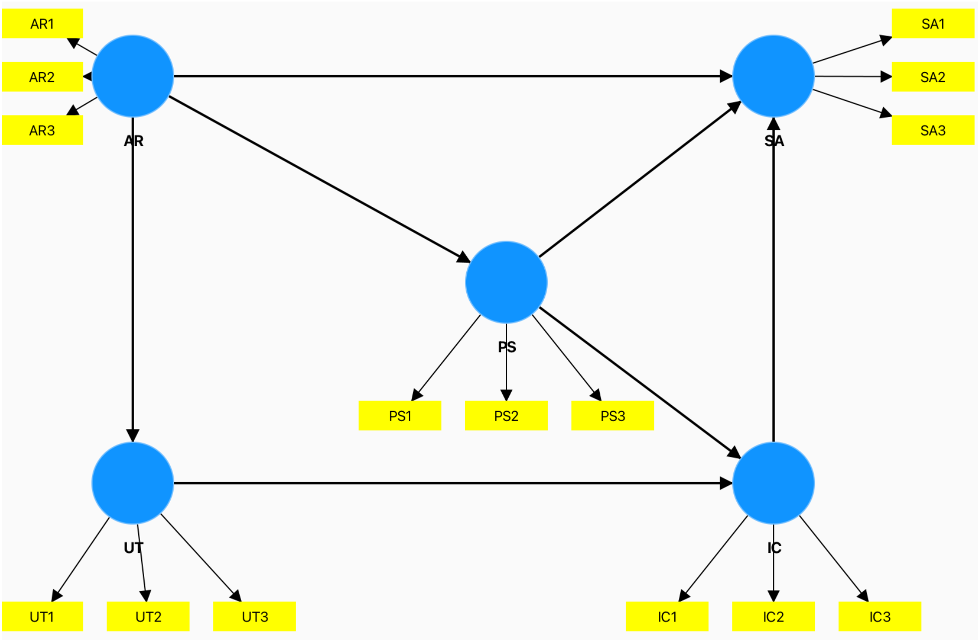

Figure 1. Conceptual Model

The conceptual model depicted in Figure 1 illustrates the relationships between key constructs essential for the adoption and implementation of circular digital economy practices, using the Smart Partial Least Squares (SmartPLS) method. It includes Antecedent Relationships (AR) with variables AR1, AR2, and AR3, which set the foundational context by representing factors such as resource availability and technological readiness. Sustainability Awareness (SA), measured by SA1, SA2, and SA3, highlights the level of awareness regarding sustainability issues among stakeholders, influenced by antecedent factors and impacting other constructs. Policy Support (PS), indicated by PS1, PS2, and PS3, reflects the degree of governmental and regulatory support, influenced by both antecedent relationships and sustainability awareness. User Technology Acceptance (UT), with UT1, UT2, and UT3, captures the readiness of users to adopt digital technologies, driven by policy support and sustainability awareness. Finally, Implementation Challenges (IC), measured by IC1, IC2, and IC3, represent the barriers faced during the transition to a circular digital economy, influenced by user technology acceptance and policy support. This interconnected model underscores the importance of cross-sector collaboration and supportive policies in successfully implementing circular digital economy strategies.

3.2 Instrumen

This study uses multi-item measurements for each factor; so that you can get final results and steps like this. First, all factors and items were identified based on evidence from the literature adapted to the research context. The data sources for this research are presented in Table 1. Thus, the choice of items was made by the researcher according to the context so that the research results were as desired. After the questionnaire was created, the questionnaire link was distributed to the wider community by distributing samples via social media and directly with a sample of 768 respondents to find out their opinions and to find out whether the existing hypotheses were correct and appropriate. In the end, there were eighteen items with 5 scales starting from (1) strongly disagree to (5) strongly agree.

Table 1. Operational definition of Variables

Variabel	Definisi Operasional
Actor Readiness (AR)	Considering Actor Readiness strengthens circular digital economy strategies, enhancing waste reduction, extending product life cycles, and minimizing environmental impacts.
Use of Technology(UT)	Integrating Technology enhances resource efficiency and adapts to circular digital economy, fostering sustainable economic growth.
Industrial Collaboration (IC)	Involving Industrial Collaboration enhances cross-sector networks and resource exchange, boosting circular digital economy implementation and economic resilience.
Policy Support (PS)	Policy Support strengthens the legal framework for circular digital economy, encouraging investment and innovation toward sustainability goals.
Stakeholder Awareness (SA)	Raising Stakeholder Awareness accelerates society's support for circular digital economy practices, boosting adoption of sustainable models.

3.3 Data analysis process

A meticulous approach to data analysis is paramount to ensure accuracy and reliability. In the context of distribution data analysis, the process begins with a thorough evaluation of questionnaires to acquire usable data. It's imperative that the measurement model being scrutinized meets essential criteria, ensuring the integrity of the data employed in the analysis. Prior to utilizing SmartPLS, qualitative data undergoes conversion into quantitative data in CSV format to streamline processing efficiency. Despite limitations associated with the student license of SmartPLS, researchers can effectively utilize available features for data analysis. During the data processing phase, the Partial Least Squares-Structural Equation Modeling (PLS-SEM) method is deployed, particularly advantageous for conducting measurement instrument or statistical calculations, especially in exploratory research and theory development. The process commences with an assessment of construct validity, involving outer model testing encompassing convergent validity and discriminant validity, utilizing data collected from e-learning user respondents. Subsequent to outer model testing, inner model testing ensues, which entails testing coefficient of determination (r2), effect size (f2), predictive relevance (Q2), and T-test. The PLS method is particularly adept at analyzing complex models entailing multiple variables owing to its capability to facilitate intricate interactions between determinant variables, dependent variables, and moderating factors. Researchers can glean profound insights into the factors influencing data analysis outcomes, thereby devising superior solutions to prevailing issues. In the analysis phase, the Technology Acceptance Model (TAM) method is leveraged, considering several variables including Actor Readiness (AR), Use of Technology (UT), Industrial Collaboration (IC), Policy Support (PS), and Stakeholder Awareness (SA).

4. Results and Discussion

4.1 Measurement Model

The measurement model undergoes rigorous testing for each variable to ascertain scale determinacy and validity. This process involves establishing the proposed relationships from observed serving object variables to latent factors by extracting common variables. A measurement model with variable values exceeding 0.6 reflects the concepts of validity and reliability in measurement. Validity pertains to the extent to which a measurement tool accurately measures what it is intended to measure, while reliability refers to the consistency of measurement results provided by the same tool. Construct Validity Testing is integral to ensure that the measurement instruments employed genuinely capture the desired constructs or aspects. Factor Analysis is employed within the measurement model to identify underlying factors or dimensions of the measured variables. This analysis aids in uncovering relationships between variables and verifies that the measurement instruments encompass relevant aspects pertinent to the variables under scrutiny. Through this meticulous process, the model undergoes thorough examination to validate its accuracy and reliability, ensuring it effectively represents the intended constructs and yields insightful perspectives on the relationships between variables.

Table 2. Result Reliability and Validity

Variable	Cronbach Alpha	Composite Reliability	AVE
AR	0.775	0.795	0.867
IC	0.811	0.813	0.725
PS	0.831	0.831	0.748
SA	0.842	0.852	0.762
UT	0.763	0.792	0.677

The results of the reliability construct analysis using the SmartPLS method show very positive indications in terms of reflection of the observed variables. In particular, the Average Variance Extracted (AVE) value that has been calculated for each variable shows a fairly high level of reliability. AVE values that exceed the threshold of 0.5 consistently indicate that these variables are able to explain most of the variation in the indicators used to measure the construct. For example, the Actor Readiness (AR) variable shows an AVE value of 0.775, which indicates that around 77.5% of the variance of the indicators used to measure actor readiness in the context of a circular digital economy can be explained by the AR construct. The same applies to other variables such as Industrial Collaboration (IC), Policy Support (PS), Stakeholder Awareness (SA), and Use of Technology (UT), each of which has an AVE value that reflects a strong level of reliability in construct measurement. related constructs. This reliability is a crucial aspect in data analysis, because it guarantees that the results obtained from research are trustworthy and valid. By having consistent and reliable variables, research can gain a deeper understanding of the relationships between variables, as well as the implications of these findings in the context of a circular digital economy. These results give researchers confidence that the measurement of these variables is in accordance with the research objectives and can be relied upon in further analysis related to the implementation and impact of circular digital economy strategies. Thus, the verified reliability of the construct provides a solid foundation for conclusions and recommendations made based on data analysis.

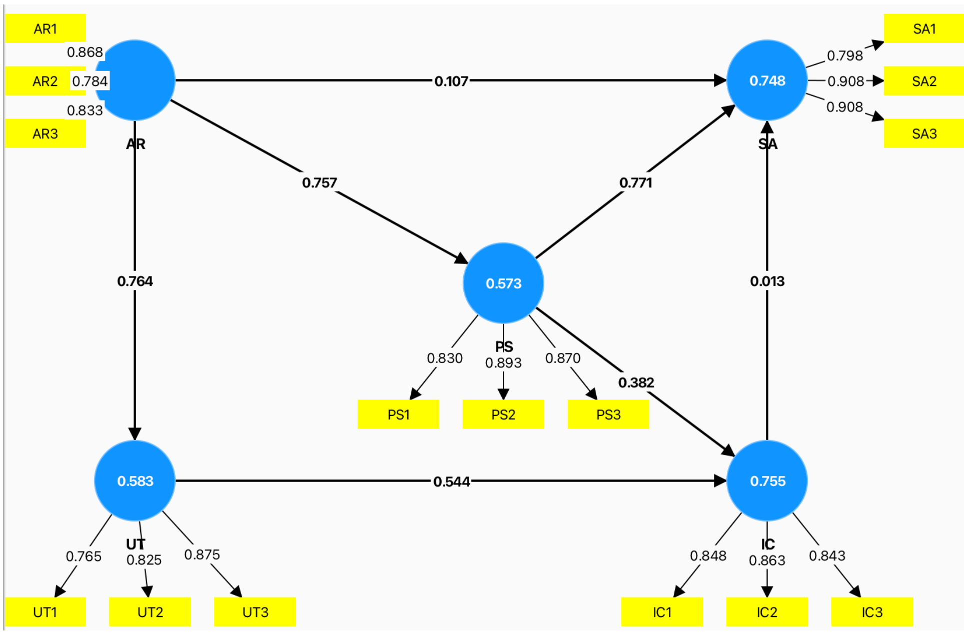

Figure 2. Conceptual model path analysis

Figure 2 presents the path analysis of the conceptual model, evaluating the relationships between constructs within a circular digital economy using Smart Partial Least Squares (SmartPLS) method. The model includes Antecedent Relationships (AR), Sustainability Awareness (SA), Policy Support (PS), User Technology Acceptance (UT), and Implementation Challenges (IC). AR significantly influences SA (0.107) and UT (0.764), highlighting its foundational role. SA, measured by high indicators (SA1, SA2, SA3), affects PS strongly (0.771), which in turn impacts IC (0.382). UT, also strongly influenced by AR (0.764), impacts IC (0.544). The minimal direct effect of SA on IC (0.013) suggests indirect influences through other variables. High R-Square values for PS (0.573) and IC (0.755) indicate the model's robustness in explaining the variance in these constructs, underscoring the importance of foundational elements, policy support, and user acceptance in successfully implementing circular digital economy practices.

Table 3. F-Square

	AR	**IC**	**PS**	**SA**	**UT**
AR			1.344	0.016	1.4
IC					
PS		0.257		0.738	
SA					
UT		0.522			

F-Square for each variable observed in the analysis using the SmartPLS method. F-Square is a measure used to evaluate the predictive power of the model that has been built for each endogenous variable (dependent variable) In the table, the F-Square values are shown in the cells corresponding to pairs of variables. For example, the value 1.344 in the cell showing

AR versus AR indicates the F-Square for the Actor Readiness (AR) variable against itself, which evaluates how well the variable can predict itself. A higher F-Square value indicates that the variable has a greater contribution in explaining its own variability or the variability of other dependent variables in the model. In your table, it can be seen that the Policy Support (PS) variable has a relatively high F-Square value relative to itself (1.400), indicating that the PS variable has a significant contribution in explaining its own variability in the context of the model being analyzed Furthermore, when looking at interactions between pairs of variables, such as AR versus IC, PS versus IC, and so on, F-Square values indicate how well one variable can predict the other variable in the model. The higher the F-Square value between two variables, the greater the contribution of one variable to explaining the variability of the other variable in the context of the model being analyzed. Thus, the F-Square table provides information about the predictive power of each variable in the model, both against itself and against other variables. This helps researchers evaluate the importance of each variable in explaining the phenomena observed in the analysis.

Table 4. R-Square

	R-Square	**R-Square Adjusted**
IC	0.755	0.75
PS	0.573	0.569
SA	0.748	0.74
UT	0.583	0.579

The SmartPLS table presented displays the R-Square and Adjusted R-Square values for each variable in the analysis model. R-Square is a measure that shows how much variation in the dependent variable (the variable you want to predict) can be explained by the independent variables (predictor variables) in the model. Meanwhile, Adjusted R-Square corrects the R-Square value for model complexity, taking approximately the number of independent variables and sample size. In this table, the Industrial Collaboration (IC) variable has an R-Square value of 0.755 and an Adjusted R-Square of 0.750. This indicates that around 75.5% of the variation in the variables used to measure industrial collaboration can be explained by other variables in the model. Likewise, the Policy Support (PS) variable has an R-Square value of 0.573 and an Adjusted R-Square of 0.569, indicating that around 57.3% of the variation in policy support can be explained by other variables in the model. Similar results are also seen in the Stakeholder Awareness (SA) and Use of Technology (UT) variables, which respectively have quite high R-Square and Adjusted R-Square values. This analysis provides insight into how well the variables in the model are able to explain variation in the dependent variable, and their influence in the context of the model being explained.

5. Conclusions

This research has yielded insightful findings regarding the effectiveness of circular digital economy strategies. Utilizing SmartPLS analysis, key conclusions can be drawn from the results obtained. Firstly, the high values of Average Variance Extracted (AVE) across all variables indicate strong reliability in measuring the constructs related to circular digital economy strategies. This suggests that the measurement instruments used effectively capture the intended concepts, laying a robust foundation for further analysis. Secondly, the significant values of F-Square for various variable pairs highlight the strength of relationships within the model. For instance, the F-Square values between Industrial Collaboration (IC) and other variables indicate substantial predictive power, emphasizing the importance of collaboration in implementing circular digital economy strategies effectively.

Furthermore, the R-Square and R-Square Adjusted values demonstrate the extent to which the variables explain the variance in the dependent variable. The high values observed suggest that the model comprising variables like Policy Support (PS), Stakeholder Awareness (SA), and Use of Technology (UT) effectively contributes to understanding and predicting outcomes related to environmental and economic prosperity. These findings underscore the critical role of policy support and stakeholder awareness in driving the successful adoption of circular digital economy practices. Additionally, the integration of technology plays a pivotal role in enhancing the efficiency and effectiveness of these strategies, further contributing to sustainable economic growth.

Building on these findings, future research could delve deeper into specific aspects of circular digital economy strategies. For instance, longitudinal studies tracking the implementation of these strategies over time could provide insights into their long-term effectiveness and sustainability. Additionally, comparative studies across different sectors or geographical regions could elucidate variations in the adoption and outcomes of circular digital economy strategies. Understanding these variations could inform tailored interventions and policies to enhance their effectiveness in diverse contexts. Moreover, exploring the moderating effects of factors such as regulatory frameworks, technological advancements, and consumer behavior could enrich our understanding of the dynamics shaping the implementation and impact of circular digital economy strategies. In conclusion, while the present study provides valuable insights into the potential of circular digital economy strategies for sustainable innovation, ongoing research is essential to address remaining gaps and challenges. By continuing to explore these avenues, we can further advance our understanding and implementation of strategies aimed at achieving environmental and economic prosperity.

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