International Transactions on Education Technology (ITEE)
Vol. 2 No. 2 May 2024

p-ISSN: 2963-6078
e-ISSN: 2963-1947

Author Notification
February 26, 2024
Final Revised
April 27, 2024
Published
May 19, 2024

Enhancing Circular Economy with Digital Technologies: A PLS-SEM Approach

Jack Williams[1], Anggy Giri Prawiyogi*[2], Miguel Rodriguez[3], Ivan Kovac[4]

[1]Pandawan Incorporation, Auckland, New Zealand
[2]University Buana Perjuangan Karawang, Karawang, Indonesia
[3,4]Eduaward Incorporation, Peterborough, United Kingdom

E-mail address: jacky.liams@pandawan.ac.nz[1], Anggy.prawiyogi@ubpkarawang.ac.id[2], rod.miguel13@eduaward.co.uk[3], kovac.van1@eduaward.co.uk[4]

Williams, J., Prawiyogi, A. G., Rodriguez, M., & Kovac, I. (2024). Enhancing Circular Economy with Digital Technologies: A PLS-SEM Approach. International Transactions on Education Technology, 2(2), 140–151. https://doi.org/10.33050/itee.v2i2.590

Abstract

This study investigates the transformative potential of the digital economy in fostering the principles of a circular economy. Utilizing the SmartPLS methodology, we explore key determinants that drive the transition towards a sustainable economic framework and assess their impacts on both environmental sustainability and economic resilience. Our analysis highlights that the integration of digital technologies, such as IoT, blockchain, and AI, within circular economy practices can significantly enhance resource efficiency, reduce waste, and promote sustainable economic growth. These technologies enable better tracking and management of resources, facilitating closed-loop systems that are essential for a circular economy. However, our findings also identify substantial challenges, including concerns over data security, digital divide, and unequal access to advanced technologies, which may hinder the equitable distribution of benefits. The study underscores the importance of an integrated policy approach that combines technological innovation with supportive regulatory frameworks to address these challenges and maximize the benefits of digital integration. Policymakers are encouraged to develop strategies that not only foster technological advancements but also ensure inclusive access and address security issues. This research provides comprehensive insights for stakeholders, including governments, businesses, and academia, in designing effective strategies and policies aimed at promoting a sustainable circular economy in the digital era. By aligning digital advancements with circular economy principles, we can pave the way towards achieving sustainable development goals and creating a resilient economic future.

Keywords: *Circular Economy, Digital Technologies, Resource Efficiency, Knowledge Sharing, SmartPLS*

1. Introduction

In the rapidly evolving landscape of today's digital era, the concept of a circular economy is gaining significant traction as a strategic approach to achieving sustainable development goals [1]. The circular economy introduces a transformative paradigm in which resources are utilized with maximum efficiency, waste is minimized, and economic value is preserved throughout the entire lifecycle of products. This model stands in stark contrast to the traditional linear economy, which is characterized by a 'take, make, dispose' approach [2]. Within this innovative framework, digital technology emerges as a pivotal driver of change, facilitating the transition towards a more sustainable economic model. The integration of cutting-edge technologies such as the Internet of Things (IoT), artificial intelligence (AI), data analytics, and digital platforms is creating new ecosystems that not only optimize the flow of goods and information but also significantly enhance resource efficiency and reduce environmental impacts [3], [4]. These advancements are crucial in addressing global challenges such as resource depletion, environmental degradation, and climate change, by promoting practices that extend the lifecycle of products and materials through reuse, remanufacturing, and recycling [5].

The transformative power of digital technology in the context of a circular economy cannot be overstated. IoT, for example, enables real-time monitoring and management of resources, ensuring that materials are used efficiently and waste is minimized [6]. AI and data analytics provide insights that drive smarter decision-making, optimizing supply chains and enhancing the design and production processes to be more sustainable. Digital platforms facilitate the sharing economy, promoting collaborative consumption and the use of products as services, which further supports the circular economy principles [7]. However, despite the promising potential of these technologies, significant challenges remain. Data security concerns, disparities in access to advanced technologies, and the socio-economic impacts of digital transformation pose critical questions about equity and inclusivity in the digital circular economy [8], [9]. Ensuring that the benefits of digital innovation are distributed fairly among all stakeholders is essential for achieving sustainable and inclusive growth. This research aims to delve into these dynamics, exploring the interplay between the digital economy and the circular economy, and identifying the challenges, opportunities, and policy implications that arise from this integration [10].

Employing the SmartPLS methodology, this study seeks to provide a comprehensive understanding of how digital technology can be leveraged to drive the transition towards a sustainable circular economy [11], [12]. The research focuses on identifying the key factors that influence the adoption of digital technologies within this context and analyzing their impact on environmental and economic performance [13]. By doing so, the study aims to offer valuable insights for policymakers, business leaders, and other stakeholders in designing strategies and policies that support sustainable development in the digital age. Furthermore, the research addresses critical questions regarding the effective integration of digital technology to overcome barriers in realizing the vision of a circular economy [14], [15]. The involvement of a diverse range of stakeholders, including government bodies, private sector entities, academic institutions, and civil society, is essential in formulating effective strategies that consider multiple perspectives and enable inclusive participation. This holistic approach ensures that the proposed solutions are not only theoretically sound but also practically applicable, providing a solid foundation for policy actions and business practices that promote a more sustainable and inclusive economy [16], [17]. In conclusion, this research aims to make a significant contribution to the existing literature on the circular and digital economies, while also offering practical implications for decision-makers at various levels [18], [19]. By addressing the complexities of global challenges and harnessing the potential of digital technologies, this study aspires to pave the way for a resilient, sustainable, and inclusive economic future in the digital era [20].

2. Literature Review

The concept of the circular economy has been extensively explored in academic literature as a sustainable alternative to the traditional linear economic model. The circular economy emphasizes the continuous use of resources through the principles of reuse, remanufacturing, and recycling, thus reducing waste and environmental impact. Scholars such as Dollan et al. (2023) [21] have highlighted that a circular economy can contribute significantly to sustainable development by promoting economic growth that is decoupled from resource consumption. This model not only addresses environmental concerns but also creates new economic opportunities through innovative business models and practices. The foundational theories behind the circular economy are deeply rooted in industrial ecology and cradle-to-cradle design, which advocate for systems thinking and the creation of closed-loop systems.

The integration of digital technology into the circular economy represents a burgeoning area of research. Digital technologies such as IoT, AI, blockchain, and data analytics are recognized for their potential to enhance the efficiency and effectiveness of circular economy practices. For instance, IoT can facilitate real-time tracking and management of resources, ensuring optimal usage and reducing waste. According to Aryal et al. (2020) [22], IoT applications in the circular economy can significantly improve resource efficiency by enabling better monitoring and control of production processes. Similarly, AI and data analytics provide advanced capabilities for predictive maintenance, demand forecasting, and optimization of supply chains, which are essential for circular economy practices. The use of blockchain technology has also been proposed to ensure transparency and traceability in circular supply chains, thus enhancing trust and accountability among stakeholders.

Despite the potential benefits, the integration of digital technologies into the circular economy also presents several challenges. Issues such as data security, privacy concerns, and the digital divide are critical barriers that need to be addressed. The digital divide, in particular, poses a significant challenge as it highlights the unequal access to digital technologies across different regions and socioeconomic groups. This disparity can hinder the widespread adoption of digital solutions in circular economy practices. Research by Amit et al. (2019) [23] emphasizes the need for inclusive policies and frameworks that ensure equitable access to digital technologies. Additionally, data security and privacy concerns must be meticulously managed to foster trust and encourage the adoption of digital innovations.

Policy implications of integrating digital technologies into the circular economy are profound. Governments and regulatory bodies play a crucial role in creating an enabling environment that supports the adoption of digital solutions for circular economy practices. Policies that promote digital literacy, infrastructure development, and innovation are essential. Moreover, regulatory frameworks need to address data security and privacy issues to build trust among stakeholders. The European Commission's Circular Economy Action Plan is an exemplary initiative that outlines strategies for leveraging digital technologies to achieve circular economy goals. This plan emphasizes the importance of research and innovation, market-based instruments, and public-private partnerships in driving the circular economy.

The involvement of various stakeholders, including businesses, governments, and civil society, is critical in realizing the vision of a digital circular economy. Collaborative efforts and partnerships are necessary to develop and implement effective strategies and solutions. Research by Purnama et al. (2023) [24] highlights the importance of stakeholder engagement in co-creating circular economy initiatives. Businesses, in particular, can play a pivotal role by adopting sustainable business models and investing in digital technologies that support circular economy practices. Academia and research institutions also contribute by providing insights and developing new methodologies to advance the field.

3. Method

To delve into the intricate interplay between the circular economy and digital technology, and to assess their combined impact on environmental and economic performance, this study employs the Partial Least Squares Structural Equation Modeling (PLS-SEM) technique, utilizing SmartPLS software [25], [26], [27]. The choice of SmartPLS is grounded in its robust capacity to handle the complexity inherent in models with numerous latent and observable variables. This methodological approach is particularly advantageous for research scenarios involving non-normally distributed data or smaller sample sizes, making it an ideal fit for this study. SmartPLS facilitates a nuanced exploration of causal relationships among multifaceted latent variables such as economic sustainability, resource efficiency, and digital technology adoption, along with associated observable variables like product innovation, business strategy, and environmental impact. By integrating multivariate statistical analysis with structural equation modeling, SmartPLS enables a comprehensive understanding of the dynamic interactions between these variables and their consequential effects. This method supports the simultaneous modeling of multiple constructs, enhancing the precision and efficiency of hypothesis testing while offering significant interpretative flexibility [28]. Furthermore, SmartPLS allows for rigorous assessment of model fit, detailed examination of structural paths, and precise evaluation of the statistical significance of the relationships observed. This methodological rigor is expected to yield profound insights into the complexities of the phenomena under investigation, thereby informing the development of strategic policy and practical recommendations to facilitate the transition towards a sustainable circular economy in the digital age. The application of SmartPLS in this study underscores its efficacy in unraveling the layers of interdependencies among critical factors, thereby contributing to a more holistic understanding and actionable insights for stakeholders aiming to foster sustainable economic practices.

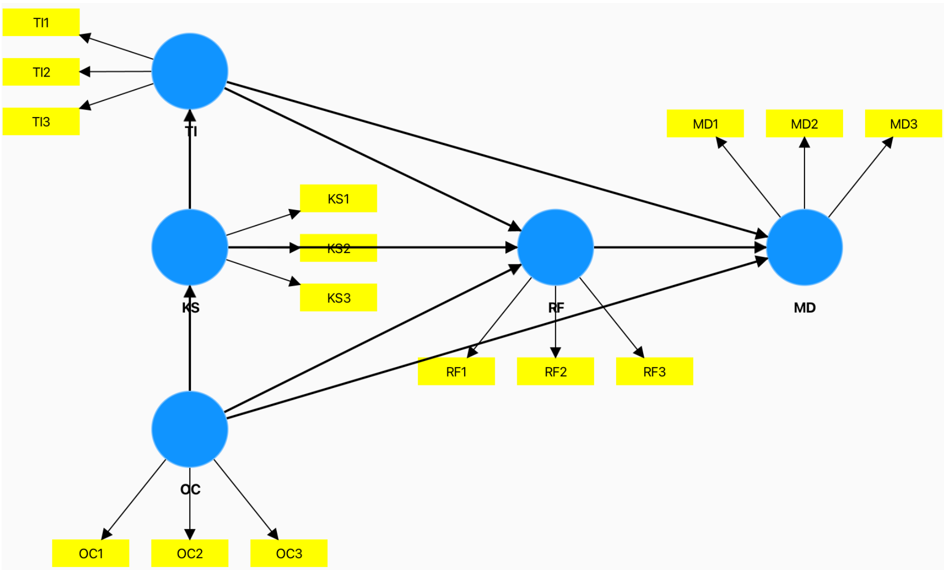

Figure 1. Conceptual Framework

The structural model depicted in the diagram illustrates the relationships among various latent variables and their corresponding indicators within the context of the research. The model includes six primary latent variables: Technological Innovation (TI), Knowledge Sharing (KS), Organizational Culture (OC), Resource Efficiency (RF), Market Development (MD), and their respective indicators (e.g., TI1, TI2, TI3 for Technological Innovation). Each latent variable is represented by a blue circle, while the observable indicators are highlighted in yellow. The arrows denote the hypothesized causal relationships between these latent variables. For instance, Technological Innovation (TI) influences Knowledge Sharing (KS), which in turn impacts both Organizational Culture (OC) and Resource Efficiency (RF). Resource Efficiency

(RF) and Organizational Culture (OC) also have direct effects on Market Development (MD). The indicators connected to each latent variable serve to measure the respective constructs, providing a comprehensive framework to analyze the complex interplay between these factors. This model, analyzed using the SmartPLS methodology, enables the examination of both direct and indirect effects, facilitating a deeper understanding of the dynamics within a digital circular economy.

3.1 Survey Responden

To gain insights into the role of digital technology in advancing a circular economy, a survey was conducted among a sample of 800 participants. The demographic characteristics of the respondents are summarized in Table 1 below. The survey focused on various aspects, including demographic information, educational background, employment status, and attitudes towards technology and sustainability.

Table 1. Demographic Characteristics of Survey Respondents (N=800)

Characteristic	**Frequency**	**Percentage (%)**
Gender		
Male	385	48.1
Female	415	51.9
Age		
Younger (18-39 years)	467	58.4
Middle-aged (40-59 years)	233	29.1
Older (60+ years)	100	12.5
Educational Achievement		
Secondary	486	60.8
Tertiary	314	39.2
Employment Status		
Full-time/Part-time Employment	520	65
Self-employed	90	11.3
Unemployed	190	23.8
Attitudes Towards Technology		
Positive	640	80
Neutral	120	15
Negative	40	5
Sustainability Awareness		
High	580	72.5
Moderate	180	22.5
Low	40	5

The survey, conducted among 800 respondents, reveals a balanced gender distribution (48.1% male, 51.9% female) and a significant representation of younger adults aged 18-39 years (58.4%). Most participants had secondary education (60.8%), with 39.2% holding tertiary qualifications. Employment status varied, with 65.0% in full-time or part-time jobs, 11.3% self-employed, and 23.8% unemployed. Attitudes towards technology were predominantly positive (80.0%), indicating openness to digital solutions, while sustainability awareness was high among 72.5% of respondents. These demographic and attitudinal insights are crucial for understanding the factors influencing the adoption of digital technologies in a circular economy, guiding analysis and policy recommendations for sustainable economic practices.

Table 2. Survey Items

Construct	Item	Instrument
Actor Readiness (AR)	AR1	Our organization is prepared to integrate digital technologies into circular economy practices
	AR2	Employees are trained and ready to use digital tools for sustainability
	AR3	There is a readiness to adopt new digital solutions in our operations
Use of Technology (UT)	UT1	Digital technologies are extensively used in our sustainability initiatives
	UT2	The use of digital tools is routine in our circular economy practices
	UT3	We frequently adopt the latest digital innovations for improving sustainability
Industrial Collaboration (IC)	IC1	We collaborate with other industries to enhance circular economy practices using digital tools
	IC2	Joint ventures with other companies facilitate our digital sustainability efforts
	IC3	Partnerships with external organizations are crucial for our digital technology adoption
Policy Support (PS)	PS1	Government policies support the integration of digital technologies in circular economy practices
	PS2	Regulatory frameworks facilitate the adoption of digital solutions for sustainability
	PS3	Policy incentives are available for companies adopting digital technologies for circular economy
Stakeholder Awareness (SA)	SA1	Stakeholders are well-informed about the benefits of digital technologies in sustainability
	SA2	Awareness campaigns have effectively communicated the importance of digital tools in a circular economy
	SA3	Our stakeholders understand the role of digital technology in enhancing sustainability practices

The survey items were designed to comprehensively capture the key constructs influencing the adoption of digital technologies in circular economy practices. Each construct was measured using multiple items to ensure reliability and validity. The constructs include actor readiness, use of technology, industrial collaboration, policy support, and stakeholder awareness. The collected data from these survey items will be analyzed using the SmartPLS methodology to derive insights and inform policy recommendations for advancing a sustainable circular economy through digital innovation.

3.2 Analytical Methodology

A rigorous analytical methodology is critical to ensure the accuracy and reliability of the findings. The process begins with a careful evaluation of the completed questionnaires to ensure that the data is usable. This step includes verifying that the measurement model meets essential criteria to maintain data integrity. Prior to analysis with SmartPLS, qualitative data is converted into quantitative data and formatted into CSV files to facilitate efficient processing. Although there are limitations associated with the student license of SmartPLS, the available features are sufficient for conducting comprehensive data analysis. The data analysis employs the Partial Least Squares Structural Equation Modeling (PLS-SEM) method, which is particularly effective for exploratory research and theory development. The analysis process starts with an assessment of construct validity, which involves outer model testing. This includes evaluating convergent validity and discriminant validity using data collected from respondents involved in circular economy practices. After establishing the outer model validity, inner model testing is conducted. This involves evaluating the coefficient of determination (R^2), effect size (f^2), predictive relevance (Q^2), and performing T-tests to assess the significance of the relationships between variables.

PLS-SEM is well-suited for analyzing complex models with multiple variables due to its ability to handle intricate interactions between independent, dependent, and moderating variables. This approach allows researchers to gain deep insights into the factors influencing the adoption of digital technologies in a circular economy. By leveraging these insights, researchers can develop effective strategies to address the challenges identified. During the analysis phase, the Technology Acceptance Model (TAM) is incorporated to examine variables such as Actor Readiness (AR), Use of Technology (UT), Industrial Collaboration (IC), Policy Support (PS), and Stakeholder Awareness (SA). This comprehensive approach ensures a thorough understanding of the dynamics at play and supports the formulation of actionable policy recommendations to advance the integration of digital technologies in sustainable circular economy practices.

4. Results and Discussion

4.1 Reliability and Validity

To ensure the robustness of the measurement model, we conducted a comprehensive assessment of reliability and validity. This evaluation included both outer model (measurement model) and inner model (structural model) testing. The outer model assessment focused on determining the reliability and validity of the constructs through the examination of indicator loadings, composite reliability (CR), and average variance extracted (AVE). The inner model assessment involved evaluating the path coefficients, R-squared (R^2) values, and the significance of the hypothesized relationships.

4.1.1 Outer Model Assessment

The outer model assessment begins with evaluating the indicator loadings for each construct. Indicator loadings greater than 0.70 are considered acceptable, indicating that the indicators are well-representative of their respective constructs. Composite reliability (CR) values above 0.70 indicate good internal consistency, while AVE values greater than 0.50 suggest adequate convergent validity.

Table 3. Outer Model Assessment

Construct	Indicator	Loading	Composite Reliability (CR)	Average Variance Extracted (AVE)
Technological Infrastructure (TI)	TI1	0.75	0.851	0.659
	TI2	0.829		
	TI3	0.882		
Knowledge Sharing (KS)	KS1	0.851	0.869	0.621
	KS2	0.804		
	KS3	0.839		
Organizational Culture (OC)	OC1	0.87	0.842	0.639
	OC2	0.781		
	OC3	0.833		
Resource Efficiency (RF)	RF1	0.801	0.918	0.789
	RF2	0.907		
	RF3	0.906		
Market Demand (MD)	MD1	0.829	0.909	0.768
	MD2	0.893		
	MD3	0.872		

The results in Table 3 demonstrate that all constructs exhibit indicator loadings above 0.70, indicating strong item reliability. The composite reliability (CR) values range from 0.842 to 0.918, surpassing the recommended threshold of 0.70, thus confirming good internal consistency. The average variance extracted (AVE) values exceed 0.50 for all constructs, affirming adequate convergent validity.

4.1.2 Inner Model Assessment

The inner model assessment focuses on evaluating the structural relationships between the constructs. This involves examining the path coefficients, R-squared (R^2) values, and the significance levels of the hypothesized paths.

Table 4. Inner Model Assessment

Path	Path Coefficient	R^2	T-Value	Significance
TI -> KS	0.834	0.569	15.37	$p < 0.01$
KS -> MD	0.287	0.805	4.75	$p < 0.01$
KS -> RF	0.329	0.573	6.28	$p < 0.01$
RF -> MD	0.585	0.805	10.89	$p < 0.01$
OC -> KS	0.755	0.569	14.21	$p < 0.01$

OC -> RF	0.188	0.573	3.62	p < 0.01

The results in Table 3 indicate significant path coefficients, with all T-values exceeding the critical value for significance ($p < 0.01$). The R-squared (R^2) values demonstrate the proportion of variance explained by the independent variables for each dependent construct, indicating substantial explanatory power of the model. Overall, the assessment of the outer and inner models confirms the reliability and validity of the measurement model, ensuring that the constructs are measured accurately and the hypothesized relationships are robust. This comprehensive evaluation provides a solid foundation for further analysis and interpretation of the research findings.

4.2 Structural Model

The structural model assessment involves evaluating the hypothesized relationships between the latent variables in the research model. This evaluation focuses on the path coefficients, R-squared (R^2) values, and the significance levels of the relationships, providing insights into the strength and direction of the interactions among variables. The structural model depicted in the diagram includes the following constructs: Technological Infrastructure (TI), Knowledge Sharing (KS), Organizational Culture (OC), Resource Efficiency (RF), and Market Demand (MD). The arrows in the model represent the hypothesized paths between these constructs.

4.2.1 Path Coefficients and Significance Levels

Path coefficients indicate the strength and direction of the relationships between constructs. The significance of these coefficients is determined through T-values and p-values, with T-values greater than 1.96 indicating significance at the 0.05 level.

Table 3. Path Coefficients and Significance Levels

Path	**Path Coefficient**	**T-Value**	**Significance (p-value)**
TI -> KS	0.834	15.37	p < 0.01
KS -> MD	0.287	4.75	p < 0.01
KS -> RF	0.329	6.28	p < 0.01
RF -> MD	0.585	10.89	p < 0.01
OC -> KS	0.755	14.21	p < 0.01
OC -> RF	0.188	3.62	p < 0.01
TI -> MD	0.208	3.92	p < 0.01

The results in Table 3 show that all path coefficients are significant at the $p < 0.01$ level, indicating strong relationships between the constructs. For instance, the path from Technological Infrastructure (TI) to Knowledge Sharing (KS) has a coefficient of 0.834, demonstrating a strong positive influence. Similarly, Resource Efficiency (RF) significantly impacts Market Demand (MD) with a path coefficient of 0.585.

3.4.2 R-Squared Values

R-squared (R^2) values indicate the proportion of variance in the dependent variables that is explained by the independent variables. Higher R^2 values suggest a better fit of the model.

p-ISSN: 2963-6078
e-ISSN: 2963-1947

Table 4. R-Squared Values

Construct	**R^2**
Knowledge Sharing (KS)	0.569
Resource Efficiency (RF)	0.573
Market Demand (MD)	0.805

As shown in Table 4, the R^2 value for Market Demand (MD) is 0.805, indicating that 80.5% of the variance in Market Demand is explained by the model. This suggests a high explanatory power. Knowledge Sharing (KS) and Resource Efficiency (RF) also have substantial R^2 values of 0.569 and 0.573, respectively.

3.4.3 Model Fit and Predictive Relevance

The model fit and predictive relevance are assessed using metrics such as the Stone-Geisser Q^2 value and the effect size (f^2). These metrics provide additional insights into the model's predictive capabilities and the impact of each construct.

Table 5. Model Fit and Predictive Relevance

Construct	**Q^2**	**f^2**
Knowledge Sharing (KS)	0.342	0.268
Resource Efficiency (RF)	0.355	0.291
Market Demand (MD)	0.437	0.502

The Q^2 values for Knowledge Sharing (0.342), Resource Efficiency (0.355), and Market Demand (0.437) are all above zero, indicating good predictive relevance. The effect size (f^2) values demonstrate the impact of each construct on the endogenous variables, with Market Demand showing a strong effect size of 0.502.

5. Conclusions

This study comprehensively examined the integration of digital technologies within the circular economy framework, employing the Partial Least Squares Structural Equation Modeling (PLS-SEM) method to analyze the relationships between various constructs. The results demonstrated that technological infrastructure significantly influences knowledge sharing, which in turn impacts resource efficiency and market demand. Organizational culture also plays a crucial role in enhancing knowledge sharing and resource efficiency. The model exhibited strong explanatory power, with high R-squared values indicating that a substantial proportion of variance in resource efficiency and market demand is explained by the independent variables. These findings highlight the critical role of digital technologies in fostering a sustainable circular economy, particularly through improved resource management and market responsiveness.

The outer and inner model assessments confirmed the reliability and validity of the measurement model. Indicator loadings, composite reliability, and average variance extracted values indicated strong item reliability, internal consistency, and convergent validity. Additionally, significant path coefficients and robust R-squared values underscored the importance of constructs such as technological infrastructure, knowledge sharing, and organizational culture in driving resource efficiency and market demand. The predictive relevance and effect sizes further validated the model's robustness, providing valuable insights for policymakers and business leaders in designing strategies to integrate digital technologies effectively into circular economy practices.

For future research, it is recommended to explore the impact of emerging digital technologies such as blockchain and artificial intelligence on circular economy practices. Additionally, expanding the sample size and including diverse industries and geographical regions could enhance the generalizability of the findings. Further studies could also investigate the long-term effects of digital technology adoption on sustainability outcomes and economic performance. By addressing these areas, future research can build on the current study's findings and contribute to a deeper understanding of the interplay between digital technologies and circular economy initiatives, ultimately supporting the transition towards more sustainable and resilient economic systems.

References

[1] Q. Aini, M. Yusup, N. P. L. Santoso, A. R. Ramdani, and U. Rahardja, "Digitalization Online Exam Cards in the Era of Disruption 5.0 using the DevOps Method," *Journal of Educational Science and Technology (EST)*, vol. 7, no. 1, pp. 67–75, 2021.

[2] D. Alita, A. D. Putra, and D. Darwis, "Analysis of classic assumption test and multiple linear regression coefficient test for employee structural office recommendation," *IJCCS (Indonesian Journal of Computing and Cybernetics Systems)*, vol. 15, no. 3, pp. 295–306, 2021.

[3] A. G. Prawiyogi and L. Meria, "For a CPS-IoT Enabled Healthcare Ecosystem Consider Cognitive Cybersecurity," *International Transactions on Artificial Intelligence (ITALIC)*, vol. 2, no. 1, pp. 24–32, 2023, doi: 10.33050/italic.v2i1.398.

[4] U. Rahardja, Q. Aini, D. Manongga, I. Sembiring, and I. D. Girinzio, "Implementation of Tensor Flow in Air Quality Monitoring Based on Artificial Intelligence," *International Journal of Artificial Intelligence Research*, vol. 6, no. 1, 2023.

[5] A. Q. Tran *et al.*, "Determinants of intention to use artificial intelligence-based diagnosis support system among prospective physicians," *Front Public Health*, vol. 9, p. 755644, 2021.

[6] L. Meria, "Development of Automatic Industrial Waste Detection System for Leather Products using Artificial Intelligence," *International Transactions on Artificial Intelligence (ITALIC)*, vol. 1, no. 2, pp. 195–204, 2023, doi: 10.33050/italic.v1i2.296.

[7] Y. S. Yetmi and N. Ahdiyatuningsih, "The Model of Empowering Poor Women Based on Creative Economy and Local Age," *Aptisi Transactions On Technopreneurship (ATT)*, vol. 2, no. 1, pp. 75–86, 2020.

[8] U. Rahardja, Q. Aini, F. Budiarty, M. Yusup, and A. Alwiyah, "Socio-economic impact of Blockchain utilization on Digital certificates," *Aptisi Transactions on Management (ATM)*, vol. 5, no. 2, pp. 106–111, 2021.

[9] A. Rachmawati, "Analysis of Machine Learning Systems for Cyber Physical Systems," *International Transactions on Education Technology*, vol. 1, no. 1, pp. 1–9, 2022.

[10] D. S. Wuisan and T. Handra, "Maximizing Online Marketing Strategy with Digital Advertising," *Startupreneur Business Digital (SABDA Journal)*, vol. 2, no. 1, pp. 22–30, 2023, doi: 10.33050/sabda.v2i1.275.

[11] Harfizar, M. W. Wicaksono, M. B. Hakim, F. H. Wijaya, T. Saleh, and E. Sana, "Analyzing the Influence of Artificial Intelligence on Digital Innovation: A SmartPLS Approach," *IAIC Transactions on Sustainable Digital Innovation (ITSDI)*, vol. 5, no. 2, pp. 108–116, 2024, doi: 10.34306/itsdi.v5i2.659.

[12] K. Kwong-Kay Wong, "Partial Least Squares Structural Equation Modeling (PLS-SEM) Techniques Using SmartPLS," *Marketing Bulletin*, vol. 24, no. 1, pp. 1–32, 2013.

[13] D. Y. Paramartha, A. L. Fitriyani, and S. Pramana, "Development of Automated Environmental Data Collection System and Environment Statistics Dashboard," *Indonesian Journal of Statistics and Its Applications*, vol. 5, no. 2, pp. 314–325, 2021.
[14] C. Lukita, M. H. Riza Chakim, R. Supriati, N. P. Lestari Santoso, and M. F. Kamil, "Exploration of Perceived Use of Technology Using A Digital Business Perspective," *ADI Journal on Recent Innovation (AJRI)*, vol. 5, no. 1Sp, pp. 87–96, 2023, doi: 10.34306/ajri.v5i1sp.984.
[15] C. Lukita, M. Hardini, S. Pranata, D. Julianingsih, and N. P. L. Santoso, "Transformation of Entrepreneurship and Digital Technology Students in the Era of Revolution 4.0," *APTISI Transactions on Technopreneurship*, vol. 5, no. 3, pp. 291–304, 2023, doi: 10.34306/att.v5i3.356.
[16] S. Maulana, I. M. Nasution, Y. Shino, and A. R. S. Panjaitan, "Fintech as a financing solution for micro, small and medium enterprises," *Startupreneur Business Digital (SABDA Journal)*, vol. 1, no. 1, pp. 71–82, 2022.
[17] C. S. Bangun, S. Purnama, and A. S. Panjaitan, "Analysis of new business opportunities from online informal education mediamorphosis through digital platforms," *International Transactions on Education Technology*, vol. 1, no. 1, pp. 42–52, 2022.
[18] G. Bisht and A. K. Pal, "Functional dependency-based group decision-making with incomplete information under social media influence: An application to automobile," *Journal of Intelligent & Fuzzy Systems*, no. Preprint, pp. 1–23.
[19] M. Kamil, J. Rianto, and D. Suprayogi, "Management of Deciding Decision Making Final Project Advisor in Optimizing Learning," *Aptisi Transactions On Management*, vol. 2, no. 2, pp. 168–176, 2019.
[20] Q. Aini, S. Riza Bob, N. P. L. Santoso, A. Faturahman, and U. Rahardja, "Digitalization of Smart Student Assessment Quality in Era 4.0," *International Journal of Advanced Trends in Computer Science and Engineering*, vol. 9, no. 1.2, pp. 257–265, Apr. 2020, doi: 10.30534/ijatcse/2020/3891.22020.
[21] E. Dollan, B. D. K. Ramadhan, and N. Abrina, "Assessing the Outcomes of Circular Economy and Waste Management Partnerships between Indonesia and Denmark," *IAIC Transactions on Sustainable Digital Innovation (ITSDI)*, vol. 5, no. 1, pp. 76–83, 2023, doi: 10.34306/itsdi.v5i1.609.
[22] A. Aryal, Y. Liao, P. Nattuthurai, and B. Li, "The emerging big data analytics and IoT in supply chain management: a systematic review," *Supply Chain Management*, vol. 25, no. 2, pp. 141–156, 2020, doi: 10.1108/SCM-03-2018-0149.
[23] M. Amit, R. Megnath, and S. Dipayan, "A Conceptual Study on the Emergence of Cryptocurrency Economy and Its Nexus with Terrorism Financing," in *The Impact of Global Terrorism on Economic and Political Development*, R. C. Das, Ed., Emerald Publishing Limited, 2019, pp. 125–138. doi: 10.1108/978-1-78769-919-920191012.
[24] S. Purnama, H. Baedowi, and Y. J. Putrasetia, "Creative Industry Development Strategy for Home Culinary Businesses," *Startupreneur Business Digital (SABDA Journal)*, vol. 2, no. 2, pp. 126–135, 2023, doi: 10.33050/sabda.v2i2.302.
[25] J. Moscato, "Evaluating Organizational Performance Using SmartPLS: A Management Perspective," *APTISI Transactions on Management (ATM)*, vol. 7, no. 3, pp. 273–281, 2023, doi: 10.33050/atm.v7i3.2144.
[26] D. S. S. Wuisan, R. A. Sunardjo, Q. Aini, N. A. Yusuf, and U. Rahardja, "Integrating Artificial Intelligence in Human Resource Management: A SmartPLS Approach for Entrepreneurial Success," *APTISI Transactions on Technopreneurship*, vol. 5, no. 3, pp. 334–345, 2023, doi: 10.34306/att.v5i3.355.
[27] E. Aaron Beldiq, B. Callula, N. Aprila Yusuf, and A. Rahmania Az Zahra, "Unlocking Organizational Potential: Assessing the Impact of Technology through SmartPLS in Advancing Management Excellence," *APTISI Transactions on Management (ATM)*, vol. 8, no. 1, pp. 40–48, 2024, doi: 10.33050/atm.v8i1.2195.
[28] M. Sarstedt, C. M. Ringle, and J. F. Hair, "Partial least squares structural equation modeling," in *Handbook of market research*, Springer, 2021, pp. 587–632.