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The Influence of the Big Data Analytics and Circular Economy on the Sustainable Performance of SMEs

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Abstract

Even though small and medium-sized enterprises (SMEs) contribute substantially to the nation's economy, they can greatly impact the environment. Hence, to achieve long-term sustainability, SMEs must consider the implementation of environmental-friendly practices. Another solution for organizations is to utilize the circular economy, including the application of digital technology, to foster growth, development, and opportunities, to achieve the sustainability of the organization. The objectives of this research were to study: 1) the influence of big data analytics on the adoption of circular economy practices in organizations; 2) the impact of circular economy practices on sustainable performance; and 3) the influence of big data analytics on sustainable performance through the implementation of circular economy practices in organizations. The researcher used a questionnaire as a data collection tool, collecting data from participants based on a purposive sampling approach. In total, 200 questionnaires were collected; the collected data were statistically analyzed and the proposed hypotheses were tested using partial least squares-structural equation model (PLS-SEM) analysis. The findings reveal that big data analytics could support the implementation of circular economy practices in organizations. In addition, the implementation of circular economy practices in the organization could increase its sustainable performance. Furthermore, it was ascertained that big data analytics could lead to sustainable performance improvement in organizations by supporting the implementation of circular economy practices.

Keywords

Big Data Analytics, Circular Economy, Sustainable Performance, Sustainable Development, Small and Medium-sized Enterprises

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Introduction

Small and medium-sized enterprises (SMEs) in Thailand play an important role in the country's economy by generating economic turnover through the distribution of income and employment. Compared to large enterprises, SMEs are the business units that add the most value to the country (TASME, 2017), with the manufacturing sector being the second most important in the economy (The Office of SMEs Promotion, 2021a). Whilst SMEs are an important part of the economy in many countries, especially developing ones (Heinicke, 2018), contributing significantly to national GDP, they also negatively impact the environment. Since most SMEs do not integrate environmentally sustainable practices into their processes, strategies, and/or long-term vision (Rita et al., 2018), they need to begin implementing more environmental-friendly practices to ensure their long-term sustainability (Malesios et al., 2020). In Thailand’s strategic plan, the Department of Industrial Promotion has given importance to sustainability in terms of the economy, society, and environment by adopting sustainable development goals (SDGs) as guidelines for sustainable development by SMEs (Department of Industrial Promotion, 2019). It seems that the spread of COVID-19 will greatly impact the sustainability of each aspect of SMEs in the manufacturing industry, where production has slowed down or even stopped. While a positive impact on environmental sustainability can be attributed to reduced greenhouse gas emissions (The National Economic and Social Development Council, 2020), it has negative economic and social impacts owing to cash shortages from reduced sales, a lack of input production, staff reduction, and loss of livelihoods (UNIDO, 2020).

The Bio-Circular-Green (BCG) concept, supported by the Thai government, establishes a new economic model for equitable and sustainable growth. Promoting BCG will result in increased biodiversity in Thailand and the capacity to apply technology and innovation to convert the country's economy into a value-based economy of goods and innovators. This aligns with the SDGs of the United Nations and Thailand's social and economic development objectives (Office of National Higher Education Science Research and Innovation Policy Council, 2022). The circular economy, which is a part of the BCG economic model, is a philosophy that aims to promote a sustainable development strategy based on the idea that goods should be used in a manner that optimizes value, is efficient, and has a life cycle with minimal environmental effect (Ellen MacArthur Foundation, 2021a). There are specific tools and approaches to achieve many of the SDGs, one of which is to use the principles of the circular economy (Schroeder et al., 2019) to achieve long-term sustainability. This approach brings resources based on "extract-produce-use-return" (Murray et al., 2017) to address the issue of the "extract-produce-use-dump" economic model of material and energy flow, which is a traditional economic model that is unlikely to be sustainable in the long term (Ibn-Mohammed et al., 2021). The circular economy concept relies on the reuse, remanufacturing, and recycling of materials and products, which results in reduced resource and energy consumption and significant cost savings (Korhonen et al., 2018). In recent years, the concept of a circular economy has received a lot of attention, and it is seen as a way to achieve sustainability at the local, national, and global levels (Schroeder et al., 2019).

According to other studies and research on the shift from a linear economy to a circular economy in SMEs, a circular economy may offer businesses a competitive advantage and aid in achieving sustainability objectives (Sharma et al., 2021). According to research on the increase in sustainability resulting from the implementation of the circular economy in SMEs, incorporation of its concepts into the company model influences the sustainability of the economy, society, and environment (Dey et al., 2020). Nowadays, digital technology is playing a growing role, where the application of artificial intelligence, the Internet of Things, and big data is creating opportunities to satisfy consumer expectations and to advance logistics and supply chain management (Witkowski, 2017). Enhancing the effectiveness of utilizing Big Data Analytics (BDA) systems stems from ensuring user satisfaction, which can be attributed to the BDA system's ability to enable successful and efficient work processes for users. This is achieved through collaborative efforts among organizational personnel, project planning and implementation pertaining to BDA, and the seamless integration of data across diverse organizational systems and BDA platforms (Chen et al., 2022). Furthermore, the utilization of the BDA system has been shown to enhance the work efficiency of operating personnel, thereby amplifying their productivity and output (Hung et al., 2021). Research on the use of circular economy principles in supply chains powered by big data has shown that organizations may increasingly utilize it to assist their decision-making processes along the supply chain. This will benefit more from managing to achieve environmental, social, and economic outcomes. Additionally, personnel who comprehend circular economy ideas and practices may leverage data-driven decision-making to attain sustainable results (Giudice et al., 2021).

For these reasons, researchers recognize the importance of studying the implementation of circular economy practices and big data analytics in organizations for the sustainable performance of enterprises in Thailand's manufacturing sector. Increasing the adoption of circular economy practices and big data analytics to improve the organization's sustainability performance should, thereby, contribute to the creation of sustainable competitive advantage for business operations. According to the natural resource-based view theory, the allocation of existing resources should be aimed at optimizing efficiency and effectiveness. Hence, the current research project involved examining circular economy practices and big data analysis that influence the sustainable performance of SMEs in Thailand's manufacturing sector. This research is divided into six sections, the first of which is the introduction. The second section is a literature review that covers the relevant ideas, concepts, and prior studies. The next sections include the research methodology, research findings, discussion, and the conclusion.

Literature Review

Circular Economy

The circular economy is a framework for resolving issues based on three principles: eliminating waste and pollution, recycling products and materials (at their maximum value), and restoring natural resources by using renewable energies and materials (Ellen MacArthur Foundation, 2021b). As proposed by producers and consumers, R strategies (Recycle, Reduce, Reuse, Recover, Repurpose, Remanufacture, Refurbish, Repair, and Rethink) are implemented within the circular economy (Kirchherr et al., 2017; Potting et al., 2017). The transformation from a traditional linear to a circular economy decouples economic activity from the consumption of limited resources. This means a systemic transformation that promotes long-term resilience for the industrial system, which enables new kinds of economic activity to enhance competitiveness, generate employment, and reduce environmental pressures (Hoogendoorn et al., 2013; Mitchell, 2015). This concept can be applied to all natural resources, both living and nonliving materials, water, and land (European Environment Agency, 2016; Su et al., 2013). All of this will contribute substantially to efforts for sustainable economic development (European Commission, 2015).

Based on the literature reviews conducted by Zhu et al. (2010) and Zhu et al. (2011), three groups of circular economy practices have been identified. Firstly, there is internal environmental management (IEM), which involves integrating environmental development into corporate strategies and assigning responsibility to middle and senior management for implementing environmentally friendly practices. However, the complexity of organizations, such as their size and stakeholder relationships, poses challenges in implementing these guidelines. Secondly, there is eco-design (ECO), which focuses on creating things with fundamental environmental considerations in mind. It aims to understand how design decisions impact product environmental compatibility. By prioritizing environmentally friendly design and considering product life cycles, organizations can offer differentiated products in the market. Lastly, corporate asset management and recovery (CAMR) or investment recovery (IR) involve reviewing the life cycle of a product to facilitate its recovery, disposal, and the sale of surplus, outdated, or end-of-life equipment. Key aspects of CAMR include product reproduction, component reuse, and raw material recovery, all of which contribute to reducing pollution and enhancing environmental and economic efficiency (Assumpção et al., 2019; Zhu et al., 2010; Zhu et al., 2011, Botezat et al., 2018; Susanty et al., 2020).

Big Data Analytics

Big data is a high-volume, high-velocity, complex, and volatile asset of information. It requires sophisticated techniques and technology for processing, capturing, storing, distributing, and managing information for improved comprehension and decision-making (Gartner, n.d.; TechAmerica Foundation, 2012. The main components of big data analytics are: big data descriptive analytics to discover and characterize what exists and the interrelationships of what exists within big data; big data predictive analytics that focuses on trends and forecasting by identifying problems to predict future outcomes or events based on existing big data; and big data prescriptive analytics, which pertains to deterministic analysis for big data sets that identifies various problems and the optimal course of action under uncertainty (Sun et al., 2015). Organizations may efficiently employ big data analytics by collecting and processing data, creating and evaluating models, and performing continuous monitoring (ur Rehman et al., 2016). Previous literature has analyzed how the utilization of big data analytics (BDA) is influenced by various factors. These factors can be categorized as follows: 1) personal factors, including rational thinking, BDA adoption openness, and BDA user satisfaction; 2) organizational factors, such as organizational readiness and the appropriate utilization of BDA in alignment with organizational objectives and culture; and 3) data factors, such as data connectivity in comparison to competitors, the presence of a centralized control system, and the implementation of open system network mechanisms to facilitate data connectivity. It is important to note that these factors not only impact the utilization of BDA but also have a significant effect on user satisfaction (Chen et al., 2022; Hung et al., 2021).

Sustainable Performance

Elkington (1997) proposed a triple bottom line idea derived from Brundtland (1987) consisting of profit, people, and planet, emphasizing the importance of measuring the worth and performance of an organization by balancing three aspects: economics, society and environment. Sustainable performance and corporate sustainability can be described in terms of the environment (Yoonprathom, 2014) as a mix of economic, social, and environmental performance. It increases productivity in terms of environmental and social contributions, while earning economic benefits. On the basis of sustainable corporate performance, businesses should address social requirements, avoid harm to the natural environment, and achieve financial objectives, with all stakeholders being given equal importance (Kocmanová & Dočekalová, 2011; Sapukotanage et al., 2018). The following encapsulates sustainable performance. 1) Economic Performance: Investors and company owners demand an increase in the company's economic efficiency. Approaches to appraisal are contingent on the current market conditions. 2) Social Performance: There are guidelines for indicators such as occupational safety, employee health, self-fulfillment and happiness, personality growth, and Corporate Social Responsibility (CSR). 3) Environmental Performance: This indicator evaluates not just the resources allocated to environmental management, but also the extent to which environmental management is integrated into operations (Kocmanová & Dočekalová, 2011; Warhurst, 2002).

Influence of Big Data Analytics on the Circular Economy

The circular economy could leverage developing digital technologies, such as big data, artificial intelligence (AI), blockchain, and the Internet of Things (IoT) (Chauhan et al., 2022). Big data efficiency is crucial for enhancing the circulation of resources in organizations using circular economy principles, thereby enhancing the effectiveness of corporate operations (Gupta et al., 2019). In addition, the supply chain driving big data analytics influences the relationship between resource management and steady performance in the circular economy (Giudice et al., 2021). According to Bag et al. (2021), the capacity of big data analytics has a direct influence on that of the circular economy. In other words, organizations with strong big data analytics capabilities have improved resource management capacity and are more capable of sustaining a healthy circular economy. This improves organizational efficiency and helps to establish a more sustainable competitive advantage. Cheng et al. (2021) reported that big data analytics have a direct effect on circular economy practices, including management systems, eco-design, and investment recovery. Additionally, they found that big data analytics had no direct effect on sustainable performance. However, circular economy practices and the resilience of sustainable supply chains are important mediator variables between big data analytics capabilities and sustainable performance. Based on the literature review, the following hypotheses were established:

Hypothesis 1 (H1): Big data analytics influence internal environmental management.

Hypothesis 2 (H2): Big data analytics influence eco-design.

Hypothesis 3 (H3): Big data analytics influence corporate asset management and recovery.

Influence of the Circular Economy on Sustainable Performance

The researcher performed a literature review to examine the impact of organizational circular economy practices on sustainable performance. The findings from several studies indicate that circular economy practices have a influence on sustainable performance.Green et al. (2012) discovered that internal environmental management has a positive direct influence on eco-design and investment recovery. In addition, eco-design and investment recovery have a direct positive influence on environmental performance and an indirect positive influence on economic performance. A study by Sezen and Çankaya (2019) found that internal environmental management has a positive influence on social and environmental performance. Similarly, investment recovery has a positive influence on social and environmental performance. In addition, Zhu et al. (2011) discovered that circular economy techniques in internal environmental management, eco-design, and corporate asset management and recovery have an effect on economic and environmental performance. Therefore, it is reasonable to hypothesize that:

Hypothesis 4 (H4): Internal environmental management influences sustainable performance.

Hypothesis 5 (H5): Eco-design influences sustainable performance.

Hypothesis 6 (H6): Corporate asset management and recovery influence sustainable performance.

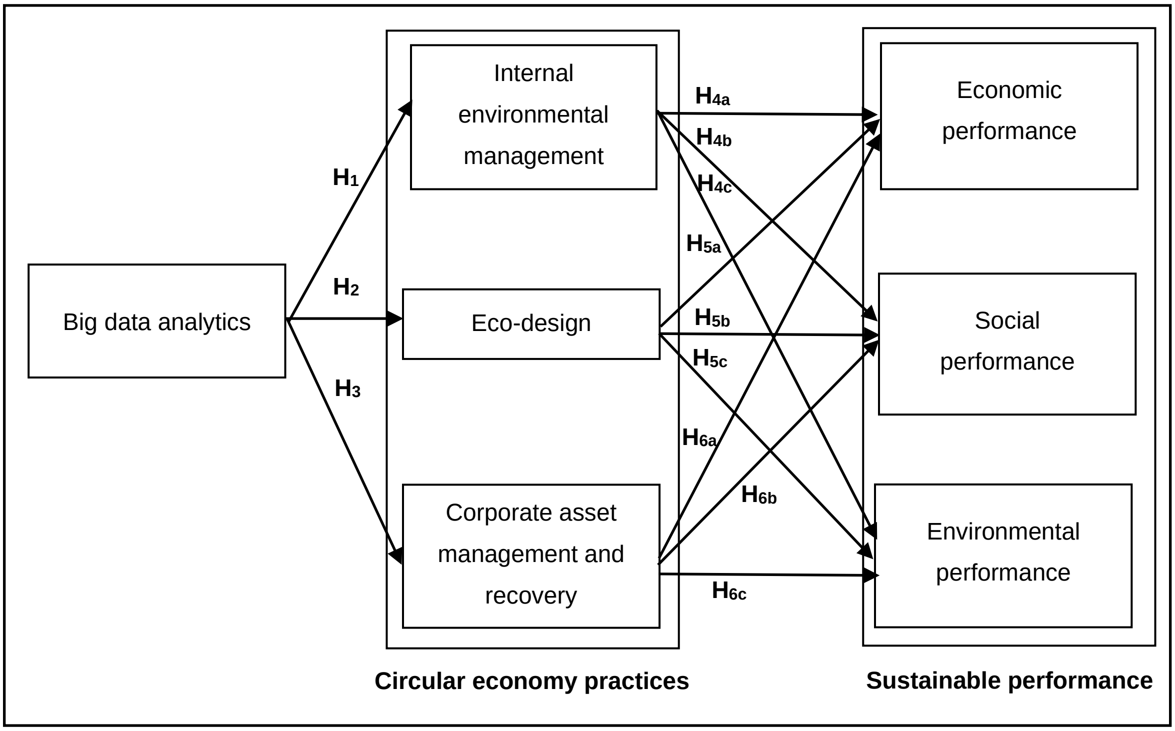

Figure 1 Conceptual framework showing proposed hypotheses.

Research Methodology

Research Design

A questionnaire was developed after reviewing the relevant literature on the circular economy, big data analytics, and sustainable performance. It posed questions that were congruent with the research aims and conceptual framework.

The primary goals of this research encompassed hypothesis testing and result analysis utilizing the partial least squares structural equation model (PLS-SEM). Subsequently, the sample size calculation approach proposed by Kock and Hadaya (2018), using the inverse square root method, was employed. The findings revealed that a minimum sample size of 155 was necessary, aligning with prior studies that suggested an optimal range of 100 to 200 participants (Hair et al., 2015; Ringle et al., 2009; Sarstedt et al., 2014).

Sample and Data Collection

In this research, we specifically focus on the food manufacturing sector due to its significant market share in Thailand and it being the largest employer among SMEs within the manufacturing industry (The Office of SMEs Promotion, 2021b). The selection of a sample group from each manufacturing sector may lead to variations in knowledge and information provided. Therefore, researchers are advised to define a sample group with similar characteristics (Sookcharoen, 2015). Accordingly, data collection was carried out from a sample group comprising of entrepreneurs and SMEs' executives from the food manufacturing sector, utilizing a non-probabilistic random sampling method. The selection of participants was based on their alignment with the research objectives, and data were collected through questionnaires (see Appendix A).

Emails with a link to the questionnaire were sent to all 2,000 entrepreneurs to collect data online. There were 117 respondents, of which 80 were identified as entrepreneurs in the food manufacturing industry (an effective response rate of 4%). At a trade fair, a link to the online questionnaire was distributed to 150 entrepreneurs, with 120 of them being entrepreneurs in the food production industry. From both methods, 200 valid samples were obtained.

The majority of respondents were self-employed (57.50%). Most had between one and three years of work experience. SMEs from across all regions of Thailand were represented in the survey, with the majority residing in the Bangkok Metropolitan area. Most of their businesses had been running for one to three years, and had incomes below 1.8 million THB, as shown in Table 1.

The circular economy practice questions were developed based on the research of Schmidt et al. (2021) and Zhu et al. (2010), whilst the big data analytics questions were developed based on the research of Bag et al. (2021). The sustainable performance questions were developed based on the research of Sezen and Çankaya (2019) and Zhu et al. (2010). A 7-point Likert scale was used to record data, with levels ranging from 1 (least practice or opinion) to 7 (most practice or opinion). In a pilot test, 35 samples were used to evaluate the questionnaire's content consistency, validity, and reliability (Javali et al., 2011; Yurdugül, 2008). The Cronbach Alpha scores for each variable were between 0.845 and 0.940, which is in the acceptable range of above 0.70 (Taber, 2018; Hair et al., 2013).

Data Analysis

The statistical partial least squares structural model (PLS-SEM) is appropriate for exploratory research with the objectives of prediction and theoretical development. This exploratory study provided understanding of the relationship between circular economy practices, big data analytics, and sustainable performance. Consequently, PLS-SEM was utilized to evaluate the reliability and validity of the framework as well as to test the hypotheses using the SmartPLS 4.0 analysis software.

Table 1 Sample demographics summary

Demographics Factor	**Descriptive Statistics**	
Job position	Business owner	115 (57.50%)
	Executive	35 (17.50%)
	Department head	29 (14.50%)
	Other	21 (10.50%)
Work experience	Under 1 year	5 (2.50%)
	1–3 years	94 (47.00%)
	4–6 years	53 (26.50%)
	More than 6 years	48 (24.00%)
Business location	Bangkok Metropolitan Region	106 (53.00%)
	Central	30 (15.00%)
	North	15 (7.50%)
	East	6 (3.00%)
	Northeast	31 (15.50%)
	West	4 (2.00%)
	South	8 (4.00%)
Period of business operation	Under 1 year	5 (2.50%)
	1–3 years	91 (45.50%)
	4–6 years	50 (25.00%)
	More than 6 years	54 (27.00%)
Yearly income of business	Not more than 1.8 million THB	135 (67.50%)
	More than 1.8 million THB but not More than 100 million THB	64 (32.00%)
	More than 100 million THB but not More than 500 million THB	1 (0.50%)

Research Findings

Measurement Model

Measurement models were assessed by testing the validity of indicators considering the standardized outer loadings of the observed variables, which should be at least 0.70 (Hair et al., 2013; Hair et al., 2014). It was found that three iterations were required to eliminate the observed variables not used in the measurement. After eliminating questions with an outer loading of less than 0.7, the final iteration results were evaluated for all remaining items in the measurement model, as shown in Table 2

Table 2 Outer loadings for indicators

Latent Variables	Observed Variables	First Iteration	Second Iteration	Final Iteration
Internal environmental management	IEM1	0.609	eliminate	eliminate
	IEM2	0.676	eliminate	eliminate
	IEM3	0.727	0.751	0.751
	IEM4	0.765	0.766	0.766
	IEM5	0.787	0.808	0.808
	IEM6	0.823	0.844	0.844
	IEM7	0.766	0.798	0.798
Eco-design	ECO1	0.824	0.823	0.824
	ECO2	0.870	0.868	0.868
	ECO3	0.860	0.862	0.862
	ECO4	0.786	0.787	0.787
Corporate asset management and recovery	CAMR1	0.695	eliminate	eliminate
	CAMR2	0.753	0.746	0.747
	CAMR3	0.797	0.803	0.803
	CAMR4	0.831	0.848	0.848
	CAMR5	0.733	0.770	0.771
Big data analytics	BDA1	0.559	eliminate	eliminate
	BDA2	0.633	eliminate	eliminate
	BDA3	0.666	eliminate	eliminate
	BDA4	0.716	0.633	eliminate
	BDA5	0.828	0.867	0.861
	BDA6	0.813	0.861	0.860
	BDA7	0.819	0.885	0.890
	BDA8	0.804	0.854	0.861
	BDA9	0.831	0.866	0.873
	BDA10	0.788	0.837	0.847
Economic performance	ECP1	0.815	0.822	0.822
	ECP2	0.841	0.842	0.842
	ECP3	0.855	0.850	0.850
	ECP4	0.846	0.842	0.842

Table 2 Outer loadings for indicators (continued)

Latent Variables	Observed Variables	First Iteration	Second Iteration	Final Iteration
Social performance	SOP1	0.633	eliminate	eliminate
	SOP2	0.807	0.815	0.815
	SOP3	0.800	0.836	0.836
	SOP4	0.722	0.716	0.715
	SOP5	0.757	0.770	0.770
Environmental performance	ENP1	0.803	0.846	0.846
	ENP2	0.816	0.846	0.846
	ENP3	0.817	0.833	0.833
	ENP4	0.686	eliminate	eliminate

Note: IEM=Internal environmental management, ECO=Eco-design, CAMR=Corporate asset management and recovery, BDA=Big data analytics, ECP=Economic performance, SOP=Social performance, ENP=Environmental performance.

The reliability of the questionnaire was determined using Cronbach's Alpha and composite reliability. Convergence validity was confirmed using the average variance extracted (AVE), the Fornell-Larcker criterion, and the Heterotrait-Monotrait (HTMT) ratio. The acceptable values for Cronbach's alpha and composite reliability were greater than 0.7 (Hair et al., 2013), both of which were higher than the recommended thresholds (the minimum values for Cronbach's alpha and composite reliability were 0.791 and 0.865). The acceptable values for the AVE values must not be lower than 0.5 (Hair et al., 2013; Hair et al., 2014) for convergence validity. As shown in Table 3, the current study had AVE values ranging from 0.617 to 0.749. To determine discriminant validity, the square root of the AVE was calculated using the Fornell-Larcker criterion, where the evaluated value must exceed the structural correlation (Gaskin and Lowry, 2014; Hair et al., 2014). The results shown in Table 4 indicate that structural separation was not a concern in this study. Additionally, the HTMT ratio was analyzed to determine whether it was below the 1 threshold (Henseler et al., 2009) and the highest HTMT observed was 0.712, as shown in Table 5.

Table 3 Results of reliability and validity tests

Construct	Cronbach's Alpha	Composite Reliability	Average Variance Extracted
IEM	0.853	0.895	0.630
ECO	0.856	0.903	0.699
CAMR	0.806	0.871	0.629
BDA	0.933	0.947	0.749
ECP	0.860	0.905	0.704
SOP	0.791	0.865	0.617
ENP	0.795	0.879	0.709

Note: IEM=Internal environmental management, ECO=Eco-design, CAMR=Corporate asset management and recovery, BDA=Big data analytics, ECP=Economic performance, SOP=Social performance, ENP=Environmental performance.

Table 4 Fornell-Larcker criterion test

	IEM	ECO	CAMR	BDA	ECP	SOP	ENP
IEM	0.794						
ECO	0.567	0.836					
CAMR	0.297	0.474	0.793				
BDA	0.640	0.430	0.388	0.866			
ECP	0.279	0.441	0.450	0.425	0.839		
SOP	0.574	0.366	0.427	0.605	0.470	0.786	
ENP	0.448	0.482	0.506	0.419	0.452	0.412	0.842

Note: IEM=Internal environmental management, ECO=Eco-design, CAMR=Corporate asset management and recovery, BDA=Big data analytics, ECP=Economic performance, SOP=Social performance, ENP=Environmental performance.

Table 5 Heterotrait-monotrait ratio test

	IEM	ECO	CAMR	BDA	ECP	SOP	ENP
IEM							
ECO	0.667						
CAMR	0.350	0.567					
BDA	0.712	0.480	0.432				
ECP	0.322	0.507	0.523	0.472			
SOP	0.698	0.442	0.511	0.703	0.570		
ENP	0.543	0.583	0.618	0.484	0.545	0.514	

Note: IEM=Internal environmental management, ECO=Eco-design, CAMR=Corporate asset management and recovery, BDA=Big data analytics, ECP=Economic performance, SOP=Social performance, ENP=Environmental performance.

Structural Model

Hypotheses regarding the structural models were investigated using Partial Least Squares Structural Equation Modeling (PLS-SEM). Path coefficient and structural model correlation analysis were tested by the Bootstrapping technique using SmartPLS 4.0 analysis software. The findings of the path coefficient analysis reveal a positive influence of BDA on all CE practices, as shown in Figure 2 and Table 6. IEM had a positive influence on social and environmental performances, ECO had a positive influence on economic and social performance, while CAMR had a positive influence on all sustainable performances. CAMR had a stronger influence on economic performance than ECO. IEM had a stronger influence on social performance than CAMR. Finally, IEM had a stronger influence on environmental performance than ECO, but less than CAMR. Moreover, the positive influence of big data analytics on all circular economy practices seems to be the foundation of sustainable performances. In addition, Table 7 shows that big data analytics had a positive indirect influence on sustainable performance through circular economy.

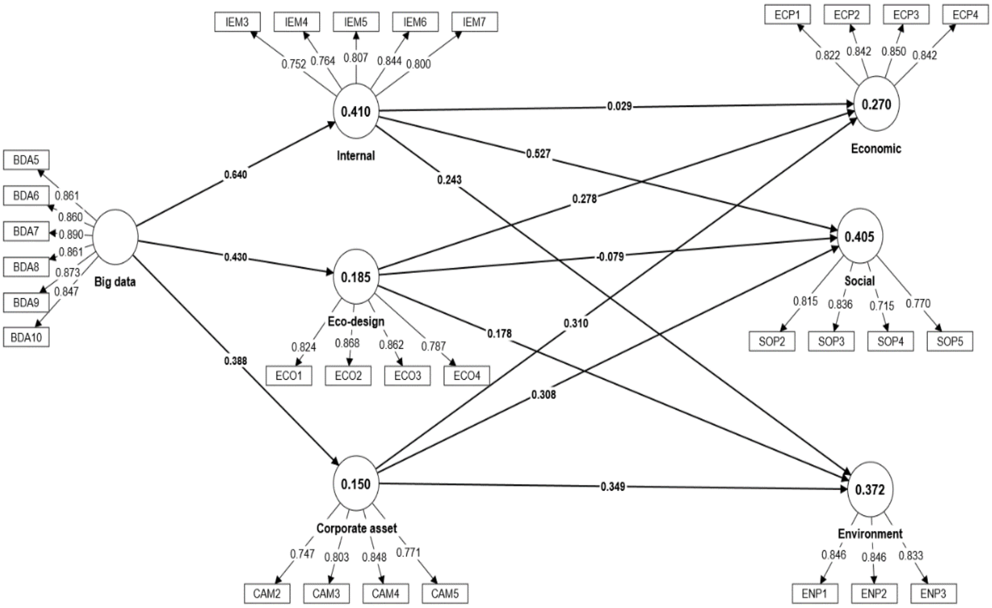

Figure 2 Structural model

Table 6 Findings from the structural model (direct effects)

Hypothesis	Relationships	Path Coefficients	t-values	p-values	Results
H1	BDA -> IEM	0.640	12.605	0.000**	Supported
H2	BDA -> ECO	0.430	4.520	0.000**	Supported
H3	BDA -> CAM	0.388	4.490	0.000**	Supported
H4a	IEM -> ECP	0.029	0.323	0.747	Not Supported
H4b	IEM -> SOP	0.527	5.626	0.000**	Supported
H4c	IEM -> ENP	0.243	2.810	0.005**	Supported
H5a	ECO -> ECP	0.278	3.122	0.002**	Supported
H5b	ECO -> SOP	-0.079	0.834	0.404	Not Supported
H5c	ECO -> ENP	0.178	2.202	0.028*	Supported
H6a	CAM -> ECP	0.310	3.871	0.000**	Supported
H6b	CAM -> SOP	0.308	4.022	0.000**	Supported
H6c	CAM -> ENP	0.349	5.386	0.000**	Supported

Note: This table reports the path coefficient between the variables and the results of the hypothesis. *, and **, denote significance at the 5%, and 1% levels, respectively. IEM=Internal environmental management, ECO=Eco-design, CAM=Corporate asset management and recovery, BDA=Big data analytics, ECP=Economic performance, SOP=Social performance, ENP=Environment performance.

Table 7 Findings from the structural model (indirect effects)

Relationships	Path Coefficients	t-values	p-values
BDA -> IEM -> ECP	0.018	0.321	0.748
BDA -> ECO -> ECP	0.119	2.210	0.027*
BDA -> CAM -> ECP	0.120	2.523	0.012*
BDA -> IEM -> SOP	0.337	4.527	0.000**
BDA -> ECO -> SOP	-0.034	0.839	0.401
BDA -> CAM -> SOP	0.119	2.590	0.010**
BDA -> IEM -> ENP	0.156	2.670	0.008**
BDA -> ECO -> ENP	0.077	2.091	0.037*
BDA -> CAM -> ENP	0.136	3.706	0.000**

Note: This table reports the path coefficient between the variables. *, and **, denote significance at the 5%, and 1% levels, respectively. IEM=Internal environmental management, ECO=Eco-design, CAM=Corporate asset management and recovery, BDA=Big data analytics, ECP=Economic performance, SOP=Social performance, ENP=Environment performance.

Discussion

The research findings show that big data analytics influenced every aspect of circular economy practices, thus indicating that they support the implementation of circular economy practices in Thai SMEs. The environment of big data analytics will foster collaborative relationships that are data-driven between supply chain stakeholders. Implementing the circular economy effectively is important. Therefore, data-driven decision-making platforms should be a requirement for supporting supply chain circular economy strategies (Gupta et al., 2019; Jiao et al., 2018). SMEs' managers and practitioners in the manufacturing sector should consider incorporating the capabilities of big data analytics into circular economy practices to create a data-driven environment to process large amounts of data collected throughout product and process life cycles, alongside sustainable and resilient relevant data (Cheng et al., 2021). The processed data may assist in the decision-making process of managers satisfying organizational expectations, as well as improving the circular economy practices of the organization (Stekelorum et al., 2021).

The findings regarding circular economy practices on sustainable performance in Thai SMEs show that internal environmental management positively influenced social and environmental performance, but had no influence on economic performance, because when organizations need to alter their operations internally, this severely limits their opportunities and results in increased operating costs, which has a detrimental impact on economic performance (Sezen & Çankaya, 2019). Environmental practices can generate economic benefits both in the short and long term (Bowen et al., 2006). Eco-design influenced economic and environmental performance, but not social performance. Eco-design involves selecting the appropriate materials and designing products for recycling, reuse, and remanufacturing, with the challenge for management being to ensure that all parties involved, including suppliers, recyclers, employees, and consumers, have the necessary knowledge and understanding to achieve these goals. This might be the reason why eco-design has no influence on social performance (Green et al., 2012; Zhu et al., 2011). When manufacturers recycle (or sell) excess materials and unused equipment, they can generate income in addition to the sale of their main goods. This approach can reduce environmental pollution caused by waste materials and the wasting of unnecessary resources. It can also improve the organizational environment, employee satisfaction, and corporate reputation (Lu et al., 2018; Sezen and Çankaya, 2019; Zhu et al., 2011).

Theoretical Contributions

This study contributes to the literature on corporate sustainability performance by proposing a new model based on the application of the literature on big data analytics, circular economy practices, and sustainable performance in the SMEs context. Furthermore, the research aligns with the natural resource-based view theory, which posits that SMEs can cultivate competitive advantages by developing capabilities in pollution prevention, product stewardship, and sustainable development. The eco-design approach enables product stewardship to achieve economic performance goals, hence reducing lifecycle costs. However, the SMEs' sustainable development must be completely sustainable in all aspects over the long term. In addition, the organization's adoption of big data analytics is a resource that may assist in generating a competitive advantage and as it is a technological resource, it may also help in creating new opportunities. Organizations must incorporate this with their other resources. In sum, big data analytics should be utilized to support the adoption of the circular economy approach aimed at improving sustainability within an organization in line with natural resource-based theory, thereby raising SME competitiveness and economic capacity.

Managerial Implications

This research provides recommendations for improving the efficacy of big data analytics in promoting the adoption of circular economy practices and achieving sustainable performance. It is crucial for organizations to impart fundamental knowledge about big data analytics to all employees and cultivate a deeper understanding among practitioners directly engaged in relevant areas. This is particularly important as many SMEs lack the necessary knowledge and tend to inefficiently utilize available resources (Iqbal et al., 2018). In addition, there must be organizational readiness and identification of the factors that need improvement to upgrade production. SMEs should develop a big data analytics project, with input from experts to guide employees so that they can strictly implement actions to achieve the objectives of the project. This will contribute to the organization's long-term performance sustainability. Nowadays, there is constant change in both consumer needs and available resources. Organizations should develop the use of big data analytics to assist them in adapting to consumer needs and changing resource consumption, by responding to changes in energy sources quickly, analyzing current events, and forecasting what will happen in the future. Furthermore, organizations should establish big data analytics projects to achieve their goals. These projects should be reviewed regularly so they are able to to stay up to date with changes in the business environment. Moreover, SMEs should enhance their utilization of big data analytics to promote increased recycling efforts. By analyzing data, SMEs can identify underlying issues and determine the necessary actions to achieve improved outcomes in recycling practices. SMEs should prioritize internal environmental management to enhance their social and environmental performance. This can be achieved by strengthening the internal performance evaluation system and compiling environmental reports for internal assessments. SMEs should develop strategic, long-term plans, as well as policies and practices that have a positive impact on the environment. Additionally, SMEs should provide environmental training to employees to improve their performance and foster a continuous learning mindset. In terms of eco-design development, which influences the organization's economic and environmental performance, the focus should be on process design to minimize waste through careful planning and the implementation of quality standards. Product design should be optimized to reduce material and energy consumption by reevaluating the product composition, leading to waste reduction. Employees should be encouraged to contribute ideas and guidelines for product design. Similarly, in the realm of asset management and recovery, organizations should establish effective recycling systems. Long-term sustainability can be supported through government policies and financial incentives that encourage enterprises to implement recycling systems. To enhance sustainable performance, SMEs should emphasize the collection and recycling of end-of-life products and materials, ensuring proper sorting and management. Moreover, there should be a greater emphasis on selling unused equipment as an asset, generating revenue from its sale, reducing maintenance costs, and creating space for other operations.

Conclusion

This study involved examining how big data analytics influence circular economy practices in organizations, how circular economy practices in organizations impact sustainable performance, and how big data analytics impact sustainable performance through the implementation of circular economy practices. The study was conducted on SMEs in the food manufacturing sector. It not only found that big data analytics can help promote the adoption of circular economy practices in organizations, but also, that circular economy practices can increase their sustainable performance. Therefore, these findings contribute to the literature on the importance of circular economy practices as a mediator variable for the influence of big data analytics on corporate sustainability performance.

Limitations and Directions of Future Research

In this study, the researcher employed a questionnaire to gather data from SMEs operating in the food manufacturing sector, which was chosen due to its significant workforce and prominence within the manufacturing industry in Thailand. However, in order to enhance the comprehensiveness of the study within the manufacturing industry and broaden future findings, the researcher suggests conducting additional research encompassing diverse manufacturing sectors. Moreover, due to the limitations in data collection caused by the COVID-19 pandemic, the majority of samples were obtained from the Bangkok Metropolitan Region. To ensure that the subsequent findings more accurately reflect the role of the circular economy, big data analytics, and sustainable performance of SMEs in the food manufacturing sector, the researcher recommends collecting additional data from SMEs across all regions of Thailand.

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Appendix A Questionnaire

	Questionnaire Items	Level of Opinion
	Internal environmental management	
IEM1	The management of the environment is supported and committed by the executives.	☐1 ☐2 ☐3 ☐4 ☐5 ☐6 ☐7
IEM2	Within the organization, there is cross-functional collaboration to improve the environment.	☐1 ☐2 ☐3 ☐4 ☐5 ☐6 ☐7
IEM3	The organization provides employees with specialized training on environmental issues.	☐1 ☐2 ☐3 ☐4 ☐5 ☐6 ☐7
IEM4	The organization has total quality environmental management.	☐1 ☐2 ☐3 ☐4 ☐5 ☐6 ☐7
IEM5	The organization has pollution prevention programs such as clean production.	☐1 ☐2 ☐3 ☐4 ☐5 ☐6 ☐7
IEM6	The organization has an internal performance evaluation system that includes environmental factors.	☐1 ☐2 ☐3 ☐4 ☐5 ☐6 ☐7
IEM7	The organization provides an environmental report for internal evaluation.	☐1 ☐2 ☐3 ☐4 ☐5 ☐6 ☐7
	Eco-design	
ECO1	The organization designs products to reduce material/energy consumption.	☐1 ☐2 ☐3 ☐4 ☐5 ☐6 ☐7
ECO2	The organization designs products for the reuse, recycling, or recovery of materials and components.	☐1 ☐2 ☐3 ☐4 ☐5 ☐6 ☐7
ECO3	The organization designs products to avoid or reduce the use of hazardous products.	☐1 ☐2 ☐3 ☐4 ☐5 ☐6 ☐7
ECO4	The organization has a process design to reduce waste.	☐1 ☐2 ☐3 ☐4 ☐5 ☐6 ☐7
	Corporate asset management and recovery	
CAM R1	The organization has investment recovery or sale of excess inventory/surplus materials.	☐1 ☐2 ☐3 ☐4 ☐5 ☐6 ☐7
CAM R2	The organization has sales of scrap and used materials.	☐1 ☐2 ☐3 ☐4 ☐5 ☐6 ☐7
CAM R3	The organization has a sale of the equipment that is no longer used as an asset.	☐1 ☐2 ☐3 ☐4 ☐5 ☐6 ☐7
CAM R4	The organization collects and recycles end-of-life products and materials.	☐1 ☐2 ☐3 ☐4 ☐5 ☐6 ☐7
CAM R5	The organization has in place a recycling system for used and defective products.	☐1 ☐2 ☐3 ☐4 ☐5 ☐6 ☐7
	Big data analytics	
BDA1	The organization uses big data analytics to increase decision-making power.	☐1 ☐2 ☐3 ☐4 ☐5 ☐6 ☐7
BDA2	The organization can easily collect data from various data sources when big data analytics is implemented.	☐1 ☐2 ☐3 ☐4 ☐5 ☐6 ☐7
BDA3	The organization routinely uses visualization techniques (such as graphing, diagramming, or	☐1 ☐2 ☐3 ☐4 ☐5 ☐6 ☐7

	Questionnaire Items	Level of Opinion
	video) to assist users or decision-makers in understanding complex information.	
BDA4	The dashboard has the ability to extract data to help with root cause analysis and focus on continuous improvement.	☐1 ☐2 ☐3 ☐4 ☐5 ☐6 ☐7
BDA5	The organization leverages big data analytics to achieve longer machine life, reduced industrial waste, and faster adaptation to more efficient processes.	☐1 ☐2 ☐3 ☐4 ☐5 ☐6 ☐7
BDA6	The organization is leveraging big data analytics to achieve efficiency in resource utilization and asset utilization in a better manner.	☐1 ☐2 ☐3 ☐4 ☐5 ☐6 ☐7
BDA7	The organization is leveraging big data analytics to encourage increased recycling.	☐1 ☐2 ☐3 ☐4 ☐5 ☐6 ☐7
BDA8	By using big data analytics, the organization can adapt better to consumer demands, make better use of resources, and respond faster to changes in energy sources.	☐1 ☐2 ☐3 ☐4 ☐5 ☐6 ☐7
BDA9	The organization has a big data analytics project led by experts and everyone strictly adheres to it.	☐1 ☐2 ☐3 ☐4 ☐5 ☐6 ☐7
BDA10	The organization has a big data analytics project which is objective and regularly reviewed on the basis of an ever-adjusting business environment.	☐1 ☐2 ☐3 ☐4 ☐5 ☐6 ☐7
	Economic performance	
ECP1	The organization has a reduction in the cost of purchased materials.	☐1 ☐2 ☐3 ☐4 ☐5 ☐6 ☐7
ECP2	The organization has a reduction in energy consumption.	☐1 ☐2 ☐3 ☐4 ☐5 ☐6 ☐7
ECP3	The organization has sales growth.	☐1 ☐2 ☐3 ☐4 ☐5 ☐6 ☐7
ECP4	The organization has profit growth.	☐1 ☐2 ☐3 ☐4 ☐5 ☐6 ☐7
	Social performance	
SOP1	Increased customer satisfaction	☐1 ☐2 ☐3 ☐4 ☐5 ☐6 ☐7
SOP2	Developing greater relationships with community stakeholders such as non-governmental organizations (NGOs) and community activists.	☐1 ☐2 ☐3 ☐4 ☐5 ☐6 ☐7
SOP3	Improving employee training and education	☐1 ☐2 ☐3 ☐4 ☐5 ☐6 ☐7
SOP4	Improved occupational health and safety of employees	☐1 ☐2 ☐3 ☐4 ☐5 ☐6 ☐7
SOP5	Improved overall welfare and better conditions of stakeholders	☐1 ☐2 ☐3 ☐4 ☐5 ☐6 ☐7
	Environmental performance	
ENP1	Reduced emissions of air pollutants	☐1 ☐2 ☐3 ☐4 ☐5 ☐6 ☐7
ENP2	Emissions of waste (e.g., sewage, solid waste) come out in a reduced amount.	☐1 ☐2 ☐3 ☐4 ☐5 ☐6 ☐7
ENP3	Reduced use of hazardous or toxic materials	☐1 ☐2 ☐3 ☐4 ☐5 ☐6 ☐7

	Questionnaire Items	Level of Opinion
ENP4	Reduced frequency of environmental accidents	☐1 ☐2 ☐3 ☐4 ☐5 ☐6 ☐7

Note: IEM=Internal environmental management, ECO=Eco-design, CAMR=Corporate asset management and recovery, BDA=Big data analytics, ECP=Economic performance, SOP=Social performance, ENP=Environmental performance.