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Organizational Internal Factors and Sustainable Performance: A Serial Mediation Model

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Abstract

***Objective*:** The present study aims to explore the relationships between big data analytics capability, circular economy practices, and SMEs' sustainable performance in Pakistan. It investigates notable factors determining SMEs' sustainable performance, including employees' perceived usefulness, data-driven culture, and leadership competency mediating the mentioned relationships. ***Method*:** The study employs quantitative research based on a positivist philosophy orientation. Data were collected through a structured questionnaire distributed among the employees of 350 SMEs operating in Pakistan's different regions. ***Findings*:** The study's results demonstrated the direct effects of big data analytics capability on sustainable performance, employee perceived usefulness, and data-driven culture. Additionally, circular economy practices influence sustainable performance; employee perceived usefulness and leadership competency. Finally, the results highlighted that each relationship is subject to partial mediation, which indicates the role of employee-perceived usefulness and data-driven culture in the relationship between big data analytics and sustainable performance and employee-perceived usefulness associated with the relationship between circular economy practices and sustainable performance. ***Novelty*:** The present study highlights that all three of the previous topics are consistent and significantly contribute to the existing literature by providing a model with the main factors that determine SMEs' sustainable performance, which can be sufficient for countries' developing economies.

Keywords:

Big Data Analytics Capability;
Circular Economy Practices;
Data-Driven Culture;
Employee Perceived Usefulness;
Leadership Competency;
Sustainable Performance.

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1- Introduction

Big Data Analytics Capability (BDAC) has become imperative for firms to improve decision-making processes and operational efficiencies amidst the business and technological world [1]. BDAC is an organization's ability to capture, manage, and process data to make information available for smarter decision-making or fundamentally change how it operates. The implementation of BDAC practices into business has come to the fore as organizations request data-driven strategies. The link between BDAC and sustainable performance is increasingly understood within academic and practical contexts [2]. Sustainable performance includes a company's economic, environmental, and social aspects; it

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implies long-term business continuity while considering responsible entrepreneurship. The use of BDAC enables companies to track trends, optimize consumption, and implement more sustainable operations. For instance, waste reduction and optimized supply chains to better customer engagement through data analytics in a manner that enforces an operating model that is more sustainable for businesses. While studies exist on either the technical aspects of big data analytics or sustainability initiatives in isolation, no study suggests how a firm's technology capabilities can be used to attain its specific environmental goals [3].

Modern approaches to sustainable development have gained much attention in business and marketing practices [4]. In advancing sustainability and making new efforts to avoid waste and make the best use of resources, one of the most critical shifts in the organization's behavior is the change from a linear economy to a circular one. The key characteristic of the circular economy is the continual use of resources that are not allowed to leave the developmental "cycle." For this purpose, recycling, reuse, and revamping are common strategies for combining resources and extending product life. Thus, using circular economy practices in an organization can be viewed as sustainable performance [5]. When considering leadership competency, the willingness and qualifications of the leader can be used to push toward the use of circular economy practices [6]. Thus, a competent leader specializing in sustainability will carry these values on the team, responsible for efficiently channeling resources and actively working to implement innovations that minimize waste. A data-driven culture also grows with circular economy practices, achieving better sustainable performance [7]. Thus, the data insights are more efficiently used to underscore further activities in properly allocating resources, waste management, and product life.

Employee perceived usefulness indicates the extent to which the staff regards its work processes, tools, or practices that positively contribute to their job performance and, consequently, the attainment of the organization's goals [8]. This factor is essential as it impacts the levels of tanking interest in the job activities and involvement, resulting in organizations' staff commitment to various operations. This factor can be regarded as a notable mediating variable when analyzing the relationship between circular economy practices and sustainable performance. For example, circular economy practices frequently refer to multiple or single strategies for waste reduction combined with resource efficiency enhancement [9]. Often, the benefits of such practices are not visible and may depend, which means that employees have to switch their mindset and behavior to facilitate effective functioning. At the same time, if the latter perceive these strategies as useful for their performance and sustainability, they support and implement these schemes. Indeed, employees' perceived usefulness in such a context can result in reduced waste, enhanced resource use, and improved sustainable performance [10].

Leadership competence is additionally crucial to that extent as it relates to sustainable performance for organizations increasingly obligated to account for the triple bottom-line effects of sustainability [11]. Effective leaders communicate the importance of sustainability, engage stakeholders, and drive initiatives consistent with a long-term perspective. For instance, the leader could also be at an advantage in implementing a policy on strategic thinking or one on stakeholder engagement. This would improve organizational performance and have several positive societal and environmental outcomes. While some previous literature has focused on leadership styles as a main characteristic attribute of these same, in alternative instances, scholars have studied sustainability practices in their multitudinous dimensions [12]; by contrast, only some examine how specific leader competencies can directly result in sustainable performance outcomes and as a mediating variable.

From the perspective of information technologies, a data-driven culture has been receiving increased attention as an essential factor for competing in fast-evolving markets. The concept can be defined as the quality of an organization when its decisions are grounded on data analysis and appropriate investigations rather than perceptions and estimates [13]. In other words, a data-driven culture shifts the attitudes of the company's employees at different levels towards cooperation with data, which, in turn, promotes a habit of operating within the framework of evidence-based decision-making. The relationship between a sustainable, data-driven culture and adequate performance becomes more pronounced when intense pressure between increasing firms' profitability and social and environmental performance is intense [14]. On the one hand, companies oriented to data collection and analysis are in a favourable position due to a higher possibility of better understanding their practices, revealing inefficiencies, controlling their resources, and estimating the social and environmental burden. For instance, some patterns may not be commonly known—a firm can track its water or forest consumption, and cloud storage can upload everything to cloud services. On the other hand, the assumption needs empirical verification, as many studies focus on the benefits of data-driven practices or investigate sustainability principles without considering how a strong data culture can facilitate or reinforce sustainable performance [15].

Based on the above past literature, the following research questions are to be addressed:

RQ1: Do big data analytics capability, circular economy practices, employee perceived usefulness, leadership competency, and data-driven culture matter for sustainable performance?

RQ2: Does employee perceived usefulness mediate the relationship between big data analytics capability, circular economy practices, and sustainable performance?

RQ3: Does data-driven culture mediate the relationship between big data analytics capability and sustainable performance?

RQ4: Does leadership competency mediate the relationship between circular economy practices and sustainable performance?

The cultural context of Pakistan's hierarchical structures and collectivist values impacts how SMEs adopt and integrate big data analytics in our study. For instance, decision-making is centralized, making it very difficult, or at least challenging, to adopt innovative practices like big data analytics. Yet, once SME leaders recognize these tools' strategic value, they create an environment where employees are more likely to adopt data-driven practices [16]. Additionally, there is a critical role for regulatory factors; in Pakistan, for instance, the emerging nature of data protection rules and support for circular economy practices may create a hospitable environment for adopting big data analytics and circular economy practices or, alternatively, may be an obstacle. For instance, uncertainty regarding the regulations may give SMEs less clearance to invest in these technologies. Instead, policies that foster sustainability can be proactive enough to encourage SMEs to exploit big data for circular economy practice to innovate in a more favorable ecosystem [17].

In addition, we might see more rapid and widespread adoption of these practices among SMEs in contrast to cultural and regulatory contexts, such as more developed economies with a well-developed data protection framework, for example, and a strong emphasis on innovation. Big data analytics may find a more favorable ground in cultures that prize individualism, entrepreneurial risk-taking, and experimentation. In that sense, Pakistan's context has challenges and opportunities, but other regions will likely have different dynamics based on their cultures and regulations [18].

However, our focus in this study is on internal factors such as big data analytics capabilities (BDAC), customer engagement practices (CEP), and leadership; however, it is important to realize that external factors are also important factors to consider in formulating the context for SMEs. However, government policies are even more influential, and supportive regulations and incentives are able to enable a climate for circular economy projects [19]. For example, a policy that rewards eco-friendly innovations with tax breaks or green technologies with funding can push SMEs to get on the circular economy wagon. On the other hand, strict regulations or unclear policies will slow their progress because they will be filled with uncertainty and add costs for compliance. The SMEs are also hugely affected by market trends. The growing need for people to sustain products and practices is becoming a hotcake for SMEs to adapt to be ahead of their competitors.

This study presented many significant contributions in relation to the existing knowledge. Firstly, it filled important theoretical gaps in the literature due to utilizing an integrated framework, including the resource-based view theory, transformational leadership theory, and the technology acceptance model. Existing studies have examined similar relationships but have always studied them separately. On the contrary, this research makes it possible to unite these independent constructs in a single framework and compare them, identifying how they relate to and influence sustainable performance in SMEs. Therefore, it is possible that the resulting model can be viewed as rather unique as it provides an opportunity to understand how these variables are connected and how they affect the scope of small and medium businesses from developing countries. Secondly, the mediating role executed by employee-perceived usefulness and other mediating variables, including data-driven culture and leadership competency, has never been examined when they play the role of an integrated model. As soon as another mediator can be viewed as the data-driven culture, it is possible to presuppose that a theoretical novelty can characterize the study. In this case, one more positive outcome is that the study can be considered innovative in the methodological sense as “previous research did not simultaneously apply the following three mediators at the same time.”

2- Theoretical Foundation and Literature Review

2-1- Resource-Based View Theory

The resource-based view is a key theory in strategic management, which theorizes that competitive advantage and greatly improved performance are the results of using the organization’s resources and abilities [20]. Resources are divided into valuable, rare, inimitable, and non-substitutable [21]. Valuable resources contribute to manipulating opportunities or decreasing threats, whereas rare resources are not currently found in other organizations. Inimitable resources are difficult or impossible to copy due to special historical conditions or socially complex connections. BDAC denotes an organization’s ability to efficiently implement the use of data in the form of “vast, diverse sources of information, and machine learning applied to massive data sets for learning [22].” BDAC is a measure of a company’s ability to collect and apply big data to decision-making to improve competitiveness.

From the perspective of the RBV, BDAC is a valuable resource. Organizations that focus on and have a high capacity for analyzing big data find it easier to identify trends and improve decision-making and resource use [23]. It is particularly valuable in the organization’s interest in implementing the circular economy. Data-driven culture (DDC) is a type of organizational culture that promotes data analysis at all levels of the organization in all departments [24]. Data is not just a tool in this environment but is instrumental in molding organizational strategies and defining the actions and paths of the development of the public-sector organization. From the viewpoint of the RBV, a data-driven culture is a unique ability that can meaningfully improve the efficiency of an organization [25].

On the other hand, circular economy practices (CEP) refer to the range of strategies and initiatives implemented to reduce waste and ensure effective resource use with the help of recycling, reusing, and sustainable product development [26]. That is, CEPs are focused on turning the existing traditional linear model of the economy into a more sustainable one to reduce waste and preserve resources. From the RBV, CEP is one of the indicators of the organizational capabilities of organizations such as BDAC and LC. In such a way, these practices serve as the bridge that translates the unique resources and capabilities of the organization to the outcomes. They benefit from variables such as environmental performance and catalyze the build-up of a firm's competitive advantage in a market increasingly prioritizing sustainability [27].

2-2- Transformational Leadership Theory

The transformational leadership theory (TLT) focuses on leaders' capacity to motivate and inspire employees to change and work collaboratively toward their common goal [28]. According to this theory, transformational leaders have charisma, vision, and empathy, allowing them to transform and coordinate their teams. By promoting their vision of the future to their followers, these leaders make employees act nobly and in the interest of the whole organization rather than that of the specific departments or work groups. LC is a term that refers to a person's skills, behavior patterns, and knowledge, making him/her an effective leader who guides the team and the organization from one strategic point to another competently and professionally [29].

Furthermore, LC has the technical knowledge that allows them to change and transform the organization and the skills and abilities to solve intergroup conflicts and inspire the team from the perspective of the TLT, the alignment between LC, and the proposal for employees to work in ways that foster SP within the firm. In the competitive world, organizations must be innovative and sustainable to compete; competent leaders must be capable of guiding their organizations through this process [30]. This might be achieved by leaders working in the circular economy, which has thoughtful implications for long-term organizational benefits. This way, leaders have to have a vision in this area and be capable of providing resources and promotion for this vision. Employees are empowered by being given the capacity to work in new ways and ensuring that they are not resisting the organization's goals [31].

2-3- The Technology Acceptance Model

In the Technology Acceptance Model (TAM), employee perceived usefulness (EPU) is a significant element that drives employee acceptance of new initiatives [32]. If employees perceive that circular economy practices are useful and positively influence their work, this category is more inclined to engage positively and actively support circular economy practices [33]. The need for the concept of EPU underlines the significance of employee perception of what role the circular economy practices play in their job performance and, subsequently, in the organization's overall needs. In particular, the aspect is necessary as it depends on how much an employee is engaged in CEP. The relationship between EPU and SP in CEP is beneficial as more engaged company members encourage the practice's effectiveness [34]. The concept presupposes that employees' contribution to viewing circular economy practices is more efficient and will be aimed at improving the performance indicators of sustainability practices.

2-4- Hypotheses Development

2-4-1- BDAC

BDAC has many benefits, such as increasing one's sustainable performance. It can help the firm harness large amounts of data to reduce inefficiencies, distribute resources more effectively, and make better-informed decisions, leading to better operational performance and a decreased environmental footprint. Through this, companies can more effectively align their strategy with the desired sustainability goals and use increasingly consumer data-driven programs to match their customers' desires for more sustainable products [35]. Their shareholders may also benefit as the firm's sustainable performance reflects better on the firm and may be objectively better in practice, leading to better customer loyalty and satisfaction [36]. However, there may be downsides to putting BDAC in a central position in one's sustainability efforts. If a company focuses too much on data, it may overlook the importance of quality aspects of its operations [37]. While being environmentally sustainable is an important aspect of a firm's operations, it is not the only thing that matters. Issues such as stakeholder engagement and social responsibility are essential factors of the overall picture. It may also be expensive for a company to dedicate substantial resources towards purchasing and maintaining the BDAC, which may cause it to disproportionally focus on such tools to the detriment of other factors. While it holds promise, it is not the end-all solution to sustainable performance issues, and one has to consider the potential trade-offs. Overall, BDAC will facilitate the drawing of some insights for organizations and prove that they align with the principles of a circular economy by using innovative solutions [38].

2-4-2- CEP

The circular economy model depends on sustainability by focusing on the reuse, recycling, and responsible consumption of resources [39]. As organizations and policymakers have become increasingly concerned about sustainable practices, the relationship between circular economy practices and sustainable performance has become pivotal in academic and practical discussion. Resource efficiency and waste reduction CEP focuses on maximizing resource efficiency and minimizing the creation of waste products [40]. By reconsidering the design of products and extending their life cycles through recycling materials, organizations can considerably reduce the environmental impact. As noted, organizations employing circular practices might experience lower costs of materials and diminished waste disposal expenses, indicating their improved SP. As governments have increasingly pressured organizations with new environmental regulations, firms engaging in CEP are more likely to meet these requirements [41]. The companies can exercise control over their SP by implementing preventive circular practices, which allow them to reduce the risk of consequences caused by failure to follow regulations or liability for environmental harm.

However, one of the disadvantages of applying a circular economy is that it requires the same initial cash investment [42]. Indeed, many of the necessary technologies, processes, and training must be purchased or implemented. Thus, transforming a company into a circular model implies having sufficient investment to do so. In addition, a number of small and medium-sized enterprises might find it difficult to “establish” their financial sustainability through such a change due to a lack of sufficient funds [43]. Another argument against using a circular economy to address sustainability issues is that many companies use this approach to deceive their customers [44].

2-5- Mediating Role of EPU

The study of the interrelation between BDAC, EPU, and SP is effectively conducted using the TAM model, which is based on the postulate that the EPU highly influences the user’s engagement and acceptance of a certain technology. EPU is the relationship mediator: if employees view the technology as beneficial, they will likely engage in technologies that introduce and promote a circular economy [45]. They are also likely committed to sustainable practices and are thus likely to achieve superior SP through engagement in BDAC that builds the CEP [46]. The advocates of the introduced correlation between CEP and SP state that the former automatically boosts the latter, ensuring the efficient use of resources and reduced waste. Adopting efficient and renewable production and reusability or recycling of products reduces the environmental footprint [47].

Moreover, waste reduction and reusability are related to lower costs that benefit the organization’s financial performance [48]. Thus, firms implementing the CEP have reported that they usually exhibit better financial performance as they experience reduced material costs and increased operational effectiveness or efficiency due to recycling and waste reduction. Additionally, the circular economy fosters creativity and motivates firms to develop new products and services that fit the requirements of the economy characterized by sustainability [49]. Such innovations make the firms more competitive in the market and contribute to shaping organizational culture.

2-6- Mediating Role of DDC

In the modern world, most companies have turned to data analytics to drive business performance [50]. Consequently, it is a continuation that a DDC has the potential to enhance SP. Specifically, organizations can use data analytics to develop strategies and tactics that comply with sustainability goals, ensure waste reduction efforts, enhance energy consumption, and improve supply chain management [15]. This approach not only helps achieve operational improvements but also aids in promoting accountability and transparency, which are critical for successful SP. On the other hand, a DDC can be associated with several challenges that can hinder SP. One of the most common problems is data misuse. Additionally, data complexity can be a barrier to an inclusive work environment. Employees or leaders with appropriate data analysis skills can respect and ignore the available information and use it correctly [51] (Sonmez et al., 2020). Furthermore, data can smother innovation because the creative decision-making process is limited to data-approved options. Moreover, the data necessary for predictive analysis and tracking of waste flows, product flows, product lifecycle, etc., can facilitate recycling, optimization, and reuse of by-products and other materials, thereby achieving innovation and efficiency goals within sustainable goals.

2-7- The Mediating Role of LC

Leadership competency (LC) is able to create a culture of innovation and accountability that encourages employees to practice sustainable activities and align their actions with the organization’s long-term goals [52]. In turn, improved SP may be considered one of the benefits of the competency under consideration since the leaders convey the importance of sustainability while creating sustainable means for their achievement. However, the limitations may arise as well. These occur since, while LC may be great for improving sustainable performance, it does not affect the sustainability of that competency. Thus, the organizational structure or culture may not be supportive of long-term sustainability, or an emphasis on leadership as a driving factor for sustainable performance can result in dependence on everyday leaders who are not always consistent, especially in the case of leadership replacement [53]. As a result, the decisions for short-term gains may be made at the leaders' discretion, potentially undermining sustainable performance. While LC is crucial for promoting sustainable activities, the competency, unless accompanied by a supportive structure, is not enough to achieve sustainable improvement. Furthermore, LC can inspire their teams to develop innovative approaches to managing resources, avoiding waste, and designing sustainable products, which supports a circular economy [54]. Therefore, the concerned competency is beneficial since it enables the leaders to inspire employee practices for performance improvement [55].

Furthermore, a few specific leadership behaviors and styles helped to foster sustainability initiatives. In this context, for instance, we find that transformational leadership, assisted by traits such as inspiration, vision, and so on, becomes a key driver [56]. Active engagement of teams through articulating a compelling vision for sustainability, driving innovation, and enhancing a culture of collaboration characterizes transformational leaders. This empowers employees to become owners of sustainability initiatives, which, in turn, drives employee motivation and commitment to achieving circular economy practices. Even more so, transformational leaders are encouraged to exhibit behaviors that promote adaptive learning and flexibility, which are fundamental to dealing with the intricacies of circular economy strategy. This ability inspires and motivates us to build a shared commitment to sustainability goals and, more broadly, to align the organization's goals with broader environmental and social considerations. To counter this, ensuring that the alignment remains is critical because it helps adopt sustainability into the organizational culture and becomes a part of the organizational business strategy.

Lastly, it is also noted that transformational leadership is highly associated with sustainable performance as it promotes resource management from a proactive dimension and waste reduction, propitious to implementing the circular economy [57]. Strong communication skills, empathy, and willingness to invest in employee development attract leaders who can create an environment of innovation and ideas that improve sustainable performance. Understood as a dynamic interplay between leadership behavior and sustainability practices, this provides us with the levers to support the practice of sustainable SMEs and reinforce effective leadership to drive a circular economy.

3- Research Methodology

In order to achieve the research objectives of the present, the methodology is given the Figure 1:

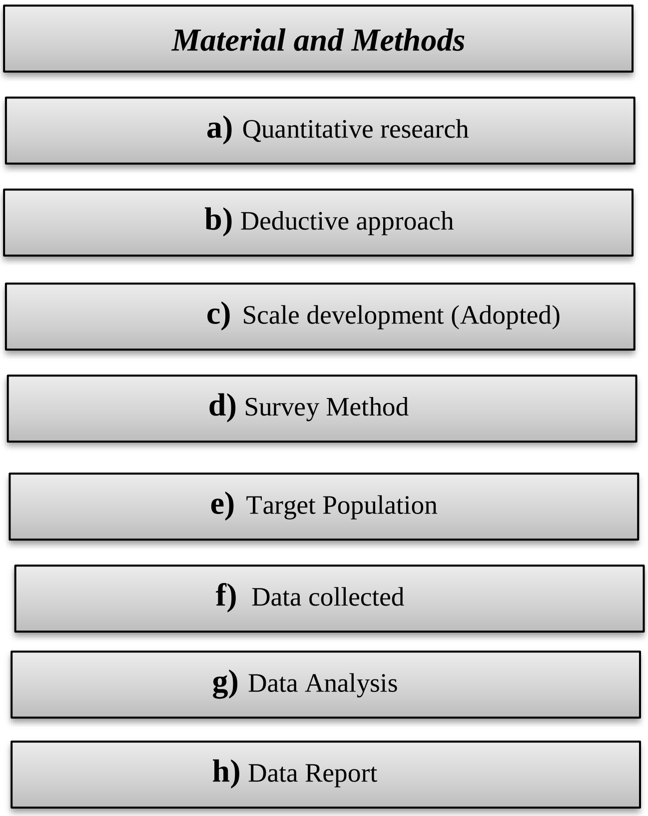

Figure 1. Material and Method

3-1- Data Procedure and Population

Quantitative research was applied in this study. A deductive research design is considered since the subject of the study is analyzed through the factors to conclude its impact on SP. A positivist philosophy is chosen since the quantitative approach is used. This philosophy supports deductive modeling, and a deductive approach is basically concerned with testing hypotheses and theories. Therefore, it is necessary to explore the relationships hypothesized and compare the existing theories, particularly the TLT and RBV, to the truths of SMEs in developing countries. A hypothesis should be elaborated to meet the requirements mentioned above. Surveys were conducted as the first research strategy to collect the necessary empirical data. The strategy is selected because of the opportunity to gather standard information from the target audience and to analyze it statistically. The primary data was collected with the help of adopted questionnaires. The questions were planned to be closed. Validated instruments were used to modify the latter, and several variables were utilized. The target population is employees working in the SME sector in Pakistan. The sampling technique was random, and the sample size was 350 people. The scale is adapted from past studies, which are discussed below from strongly agree, which equals 1, to disagree, which is equal to 5 strongly. Five-point Likert scale was considered.

3-2- Scale Development

Big Data Analytics Technology. BDAC means that a firm has the necessary tools and processes to store, manage, and analyze substantial quantities of different data types from multiple sources related to its mission. It was taken from the study of Sahoo et al. [38], and six items were considered in this study. The sample was, "Our organizations have invested in automated systems to ensure that all pertinent strategic information is always accessible throughout the lifecycle of our product and service offerings." Circular Economy Practices. CEP refers to an alternative approach that aims to minimize waste and make the most of resources through promoting resource use efficiency with the help of cycles, making them cycle processes and systems. It was taken from the study of Sahoo et al. [38], and five items were considered in this study. The sample was, "Our organization encourages visionary thinking and incentivizes technological innovation to adopt the five Rs in the supply chain. We also routinely organize education and awareness events for most of the strategic participants in the manufacturing value chain". Employee perceived usefulness: EPU is the employee's perceptual value. Employees' acceptance of a tool, technology, or practice and belief in its benefit for doing their jobs effectively is called employee-perceived usefulness. It was taken from the study of Asiri et al. [58], and six items were considered in this study. The sample was, "Using big data analytics would allow us to accomplish our work more quickly."

Data-driven culture. A DDC is one in which decisions and strategies are based on data analysis and interpretation rather than intuition or personal experience. It was taken from the study of Jeble et al. [59], and three items were considered in this study. The sample was, "We treat data as a tangible asset." Leadership Competency: LC is the knowledge, abilities, and behaviors that a leader needs to have for his or her team or organization to activate its competitive potential efficiently. It was taken from the study of Asiri et al. [58], and eight items were considered in this study. The sample was "Our leaders implement standardized procedures to ensure the continued use of big data analytics." Sustainable Performance. SP is an organization's business ability to achieve its mission and improve return on investment and reputation while reducing waste, pollution, carbon footprint, social costs, and risks over time—ensuring long-term survival and success. It was taken from the study of Jeble et al. [59], and twelve items were considered in this study. The sample was, "Our organization has adopted adequate measures for the reduction of air emissions."

3-3- Software Tool

There may be several reasons researchers prefer using SmartPLS over CB-SEM, some of which are more important than others [60]. While there are some other advantages of SmartPLS, it is more suitable for SEM research with smaller sample sizes. Therefore, researchers who have limited research experience have the opportunity to use this method, which certainly satisfies many scholars. In addition, with SmartPLS, it is also easier to use and develop complex models consisting of many other constructs and their indicators. At the same time, the data does not have to meet the requirements of a normal distribution [61]. Ultimately, there is greater freedom in using SmartPLS to analyze relationships and try models in various situations. Finally, it should be noted that SmartPLS is a better way to work with SEM than CB-SEM, especially at an early stage when research and knowledge in this area could be more efficient in working with larger sample sizes than they could have otherwise.

4- Results and Discussion

4-1- Construct Validity and Reliability

Several key metrics are employed to assess the constructs' reliability and validity: item loadings, Cronbach's alpha values, Composite Reliability, and Average Variance Extracted. Regarding BDAC, the respective item loadings vary between 0.799 and 0.855, greater than the predictable threshold of 0.70, which indicates strong item reliability. A Cronbach's alpha value of 0.905 and Composite Reliability of 0.926 imply excellent internal consistency. In addition, the AVE value of 0.677 also highlights reliable convergence based on it exceeding the threshold of 0.50. CEP showed good reliability, as evidenced by the item loadings between 0.768 and 0.849. Furthermore, Cronbach's alpha of 0.875, composite reliability of 0.909, and the AVE of 0.668 confirm the convergent validity. Regarding the EPU, the item loadings are between 0.746 and 0.851, along with a 0.902 Cronbach's alpha and a group of 0.924, which can also be considered excellent reliability. The AVE value of 0.670 suggests the adequate validity of convergence. (See Table 1 and Figure 2).

Table 1. Construct validity and Reliability

Factors	Item SPSS coding	Items loading	Cronbach alpha value	Composite Reliability	Average Variance Extraction (AVE)
Big Data Analytics Capability	BDAC1	0.848	0.905	0.926	0.677
	BDAC2	0.802			
	BDAC3	0.799			
	BDAC4	0.855			
	BDAC5	0.822			
	BDAC6	0.810			
Circular Economy Practices	CEP1	0.837	0.875	0.909	0.668
	CEP2	0.849			
	CEP3	0.831			
	CEP4	0.768			
	CEP5	0.799			
Employee Perceived Usefulness	EPU1	0.858	0.902	0.924	0.670
	EPU2	0.746			
	EPU3	0.850			
	EPU4	0.851			
	EPU5	0.774			
	EPU6	0.827			
Data driven culture	DDC1	0.846	0.830	0.898	0.746
	DDC2	0.871			
	DDC3	0.874			
Leadership Competency	LC1	0.761	0.919	0.934	0.639
	LC2	0.771			
	LC3	0.809			
	LC4	0.829			
	LC5	0.783			
	LC6	0.777			
	LC7	0.837			
	LC8	0.823			
Sustainable Performance	SP1	0.799	0.949	0.955	0.641
	SP2	0.775			
	SP3	0.832			
	SP4	0.850			
	SP4	0.833			
	SP6	0.719			
	SP7	0.791			
	SP8	0.780			
	SP9	0.836			
	SP10	0.847			
	SP11	0.823			
	SP12	0.707			

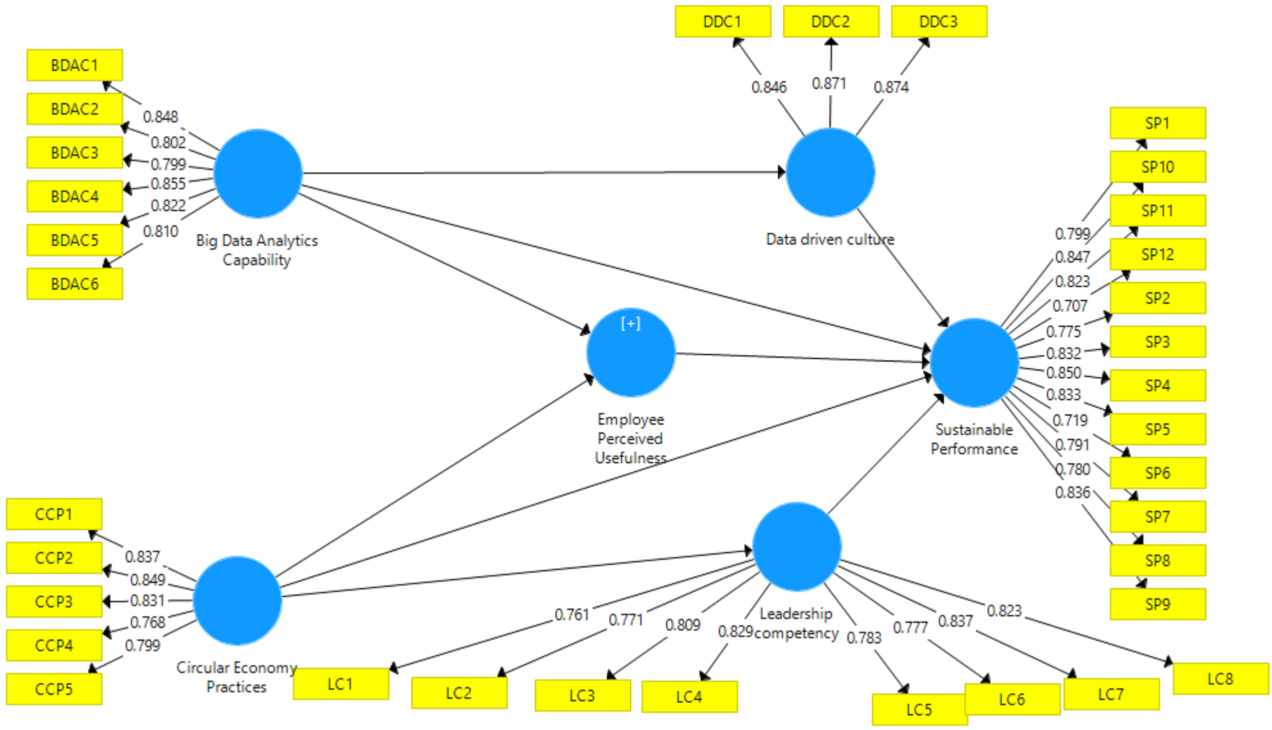

Figure 2. Measurement Model

Furthermore, DDC included item loadings between 0.846 and 0.874 and had a Cronbach's alpha of 0.830 and a Composite Reliability of 0.898; its AVE of 0.746 also suggested convergent validity. In addition, item loadings were between 0.761 and 0.837; however, Cronbach's alpha of 0.919 and a group of 0.934 indicate the strong reliability of LC. AVE of 0.639 also suggested the convergent validity. Finally, as for the SP, the item loadings are between 0.707 and 0.850, along with a Cronbach's alpha of 0.949 and a Composite Reliability of 0.955, which indicates excellent reliability. Its AVE of 0.641 also confirms convergence. Overall, all the constructs demonstrate strong reliability and validity – all of them exhibit high Cronbach's alpha values, Composite Reliability, and AME, exceeding the thresholds, which means that they are described as both consistent and possibly effective in measuring the respective constructs. (See Table 1 and Figure 1).

4-2- Discriminant Validity

4-2-1- Heterotrait-Monotrait Ratio (HTMT)

HTMT values are a highly recommended means of assessing whether discrimination among the constructs in the model is appropriate, and a critical threshold has been set for them at 0.85 and 0.90 as confirmation [62]. The HTMT value between BDAC and CEP is 0.803, below the set threshold of 0.85, confirming that these two constructs are sufficiently distinct. The discussed conclusion is also supported by the corresponding value between BDAC and DDC, which has been determined to be 0.824 and accepts the discussed notion of sufficient discriminant validity. On the other hand, the two constructs that are apparently closest in comparison are BDAC and EPU, which have produced an HTMT value of 0.801. While it is still below the established threshold, it still poses the question of their potential closeness to one another. The value between BDAC and LC is 0.817, which confirms that the two constructs are suitably differentiated from one another, and the value compared to SP is 0.807, which also fails to reach 0.85. For SP, the discussed value was produced by comparing it to BDAC. It has the characteristic of a construct that is just as distinguishable from BDAC as all other constructs, which produces the highest value at 0.753 with EPU. All the constructs have been found to maintain discrimination, and they are all mainly below 0.85, which is an even bonus for the discussed tests (see Table 2).

Table 2. Heterotrait-Monotrait Ratio (HTMT)

	BDAC	CEP	DDC	EPU	LC	SP
BDAC						
CEP	0.803					
DDC	0.824	0.739				
EPU	0.801	0.772	0.747			
LC	0.817	0.764	0.722	0.758		
SP	0.807	0.750	0.731	0.753	0.721	

4-2-2- Fornell-Larcker Criterion

The Fornell-Larcker criterion determines discriminant validity by examining the square root of the AVE for each construct, as shown in the diagonal. This value should be higher than the respective construct row and column numbers. According to the matrix, the diagonal value for BDAC is 0.823, exceeding its correlations with the other constructs: 0.786 with CEP through 0.815 with EPU. It showed that BDAC has discriminant validity. Furthermore, the relevant square root of AVE for CEP is 0.817, exceeding other correlation values: 0.749 with DDC and 0.688 with LC. Therefore, it can be concluded that the CEP construct has a proper degree of distinctiveness. At the same time, the DDC square root of AVE is 0.864, exceeding 0.654 and, similarly, 0.819 for EPU against the reduced 0.625 with BDAC. Lastly, LC has the square root of AVE at 0.799, exceeding 0.773 and 0.699. Thus, the last construct, SP, receives the value of 0.801, exceeding the correlation with BDAC at 0.769 and EPU at 0.708. Overall, with the Fornell-Larcker Criterion, all constructs have been triaged as valid for discriminant validity. They are all distinct from each other in a significant and congruous manner, showing that the measurements have validity. (See Table 3)

Table 3. Fornell-Larcker Criterion

	BDAC	CEP	DDC	EPU	LC	SP
BDAC	0.823					
CEP	0.786	0.817				
DDC	0.749	0.631	0.864			
EPU	0.815	0.696	0.654	0.819		
LC	0.773	0.688	0.635	0.699	0.799	
SP	0.769	0.685	0.650	0.708	0.678	0.801

4-3- Structural Model Assessment

4-3-1- Effect Sizes (F-Square)

BDAC has an F-square of 0.053. The analysis demonstrated a moderate effect on SP. The outcome suggests that enhancing the capabilities of data analytics to achieve business goals often has a moderate effect on overall sustainability performance. CEP has an effect of 0.021. The effects of DDC and EPU are both 0.017 and 0.027. Nonetheless, they are slightly minimal, and although the two do affect CEP, they are not direct. Lastly, the effect of LC is having an F-square of 0.018, an outcome that shows that the effect is extremely minimal in SP. As a result, from the consideration of the other constructs, the variables under review do have an effect. Nevertheless, from the obtained effect, it is evident that it is relatively minimal, and further investigation is needed to discover the exact effect under consideration.

4-3-2- Multicollinearity Assessment

The table provides the VIF for different constructs in the model, which is the most important step in assessing multicollinearity between constructs. A moderate level of multicollinearity was found in the pair between BDAC and CEP, with a VIF score of 2.606. The VIF with DDC has a count of 2.398, which means there is indeed some correlation, but it is nowhere close to very high. When tied with a DDC and CEP have a VIF score of 2.777 and report higher multicollinearity on that axis. Its VIF with itself, however, is 1.000, ensuring that it gives no multicollinearity issue. The VIF value of this construct in relation to other constructs is 2.354, and there was no collinearity issue as per Table 4. EPU has the highest VIF with 3.161, indicating significant multicollinearity relations among increasing constructs in this model. The VIF for LC is 2.694, which demonstrated some degree of multicollinearity with other constructs but remains within reasonable range values. Although some constructs showed medium levels of multicollinearity, no value for VIF is greater than 5, suggesting that the interactions between constructs can be tested without disturbing the potential disruption to results due to multicollinearity [63].

Table 4. Multicollinearity Assessment

	BDAC	CEP	DDC	EPU	LC	SP
BDAC				2.606		2.398
CEP				2.606		2.777
DDC						2.354
EPU			1.000		1.000	3.161
LC						2.694
SP						

4-3-3- R-squared and Adjusted R-squared

Table 5 summarizes the R Square and Adjusted R Square values of different constructs in the model, representing the amount of variance explained by independent variables for each dependent variable [64]. The R Square for DDC is 0.563, which means that approximately 56.3% of the variance in DDC can be explained by the predictors used in this model. Adjusted R Square is 0.561, which means this value slightly adjusts for the number of predictors that confirm our model fits well as it is closer to 1. The R Square value of EPU indicated that the independent variables explain approximately 67.4% of the variance in EPU. An Adjusted R Square of 0.671 infers that this model similarly carries considerable explanatory power after considering the number of predictors. The second line of the coefficient table, LC, has the highest R Square in model 0.475, meaning we explain 47.5% of the variance for LC through this model. The Adjusted R Square of 0.473 is better, but the best thing we can see with this model is that it fits to explain this construct. The R Square value for SP is 0.637, indicating that the predictors in the model account for about 63.7% of the variances in SP. An Adjusted R Square of 0.630 reads comparable to the above to explain sustainable performance (Table 5). In this context, the R Square values showed that the DDC, EPU, and SP models explain an immense proportion of variance. EPU presented a higher power to explain it, followed by LC with a moderate explanatory variable (see Table 5).

Table 5. R-squared and Adjusted R-squared, PLS Predict (Q^2) and Model Goodness of Fit

R-square & R-square adjusted.		
	R-square	**R-square adjusted**
DDC	0.563	0.561
EPU	0.674	0.671
LC	0.475	0.473
SP	0.637	0.630
PLS Predict (Q2)		
	Q^2predict	
DDC	0.416	
EPU	0.440	
LC	0.298	
SP	0.403	
Model Goodness of Fit (GOF)		
	Saturated model	**Estimated model**
SRMR	0.060	0.087
NFI	0.736	0.730

4-3-4- PLS Predict (Q^2)

Table 5 shows PLS prediction analysis Q^2 values, showing the predictive quality of the models for each construct. DDC has a Q^2 value of 0.416, indicating strong predictive relevancy, again showing that the model accurately predicts changes in this construct. The Q^2 value was highest for EPU is 0.440, indicating a strong predictive performance that can successfully predict changes in Y from the X variables. For LC, the Q^2 value is 0.298 and indicates only a moderate predictive power; therefore, although still significant, the model can anticipate changes in LC, but it performs less well than the other constructs. SP also has a Q^2 value of 0.403, an acceptable predictive relevance, indicating that the model does well at predicting variations here. The results, overall, indicated that the DDC and EPU models are robust, the LC model is moderately relevant, and SP has strong prediction capabilities.

4-3-5- Model Goodness of Fit (GOF)

Model Goodness of Fit metrics help us understand how well these models fit together through some of our key metrics [65]. A normed fit index (NFI) value of 0.736 was obtained for the model, which is an indication of an acceptable fit as it falls above the commonly used cut-off criteria of > 0.70 [66]. This indicated that the model is relatively good at capturing the relationships between constructs. The estimated model's NFI is somewhat lower, which is 0.730, too, but it still can be considered moderate (acceptable). The standardized root mean square residual (SRMR) of 0.060 for the saturated model is below the cut-off at 0.087 and indicates a good fit. This indicates that the model fits well and represents the relationships between constructs, explaining that as much of the variance, observed values account for little variability in estimates (see Table 5).

4-4- Direct Effects

H1: The relation between BDAC and SP is significant (β =0.316; P=3.989); thus, hypothesis one is accepted. This indicated that improvements within this organizational construct and BDAC lead significantly to SP outcomes. *H2:* A strong relationship exists between BDAC and EPU, with a beta value of 0.702 and a t-statistic of 14.208. This high level of adoption confirmed that employees are influenced by the added value provided by these tools once their organizations raise the bar so they can be more effective. *H3:* The high impact of BDAC on the development of a DDC with beta = 0.750, and the t-statistic value is highly significant (t=27.574). Developing end-to-end analytics capabilities is essential to creating a data-driven decision-making culture. *H4:* There is a direct and positive relationship between CEP and SP (β=0.145, t-statistics=2.468). However, employing circular economy practices would be as powerful a factor in an organization's sustainability goals as big data capabilities. *H5:* Additionally, CEP significantly affects EPU (β=0.145, t= 2.793). Hence, it is supported that such practices contribute to employee-perceived instrumentality. *H6:* The hypothesis related to the effects of CEP on LC is also being supported, with the absolute direct effect of the independent variable on the dependent variable at 0.689 and the t-value at 21.786. This suggests that involvement in circular economy efforts significantly improves the leadership in the organization. *H7:* EPU positively relates to beta value= 0.177, t = 2.632 SP. When employees see resources and practices as useful, it drives sustainable organizational performance. *H8:* The t-statistic is 2.469 DDC impact on SP with beta value= 0.120. It indicated that data-centricity in the organizational culture is beneficial for sustainability initiatives. *H9:* Finally, the relationship between LC and SP is supported with β = 0.134 and t = 2.330. This indicated that sustainable performance in organizations is one of the main elements affected by successful leadership (see Table 6 & Figure 3).

Table 6. Direct effects

Path directions (Direct Effects)	Beta	Standard Deviation	T Statistics	Remarks
Big Data Analytics Capability → Sustainable Performance	0.316	0.079	3.989	Accepted
Big Data Analytics Capability → Employee Perceived Usefulness	0.702	0.049	14.208	Accepted
Big Data Analytics Capability → Data-driven culture	0.750	0.027	27.574	Accepted
Circular Economy Practices → Sustainable Performance	0.145	0.059	2.468	Accepted
Circular Economy Practices → Employee Perceived Usefulness	0.145	0.052	2.793	Accepted
Circular Economy Practices → Leadership Competency	0.689	0.032	21.786	Accepted
Employee Perceived Usefulness → Sustainable Performance	0.177	0.067	2.632	Accepted
Data-driven culture → Sustainable Performance	0.120	0.049	2.469	Accepted
Leadership competency → Sustainable Performance	0.134	0.057	2.330	Accepted

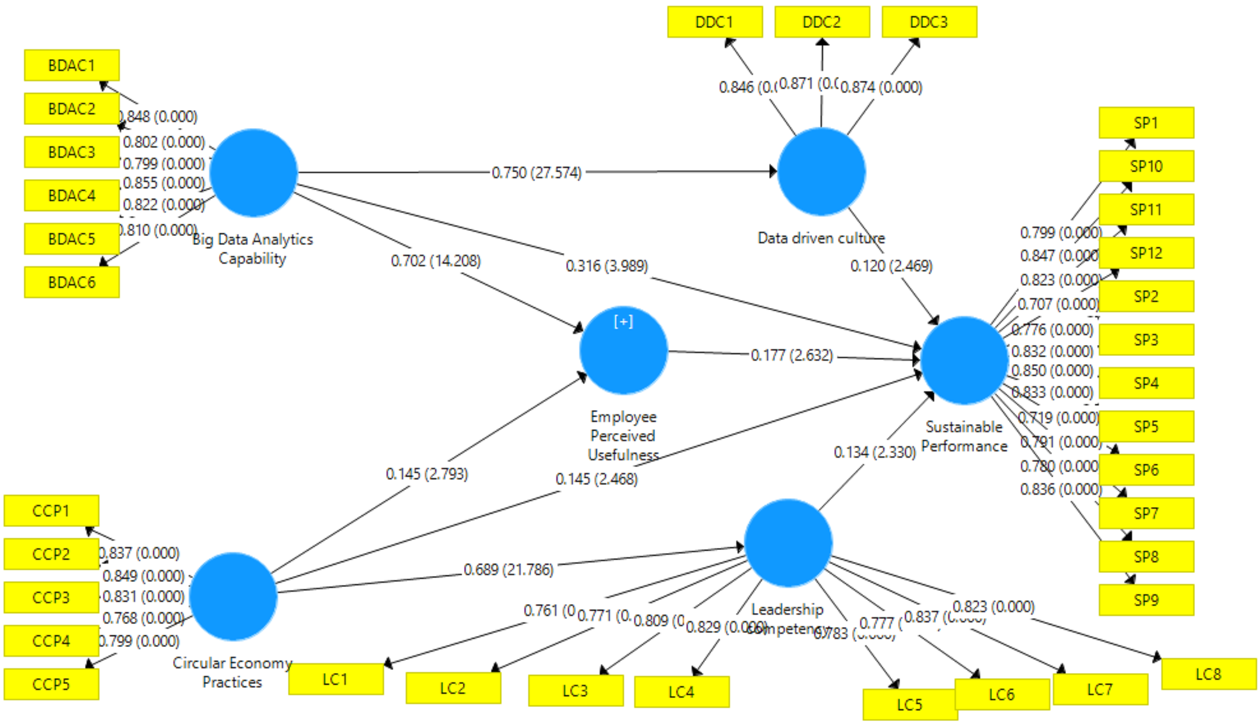

Figure 3. Structural Model

4-5- Indirect Effects (Mediating Effect)

H10: BDAC and SP have a significant follow-up effect when EPU is a meditator factor, with a beta value of 0.124 and t-statistics of 2.564. Interpretation of BDAC usage is a powerful tool that contributes to firm success; however, the direct influences are also significant, so indirect effects are partially affected. *H11:* The indirect effect of CEP on SP through EPU is insignificant (beta = 0.026, t = 1.943). This suggests a full mediating impact, and the utility of CEP positively affects SP. *H12:* The beta of the indirect effect of BDAC and SP via DDC is also significant (0.09, 2.425). It revealed that it was partially mediated by a DDC fostered by management, supporting the idea that having and leveraging BDAC contributed directly to SB. *H13:* The indirect effect of CEP on SP through LC is denoted by beta value = 0.278 (t-statistic =7.163). Our results suggested that circular economy initiatives can enhance leadership skills, facilitating increased SP (see Table 7 and Figure 3).

Table 7. Indirect Effects (Mediating Effect)

Path directions (Indirect Effects)	Beta	Standard Deviation	T Statistics	Remarks
Big Data Analytics Capability → Employee Perceived Usefulness → Sustainable Performance	0.124	0.048	2.564	Partial Meditation effect
Big Data Analytics Capability → Data-driven culture → Sustainable Performance	0.090	0.037	2.425	Partial Meditation effect
Circular Economy Practices → Employee Perceived Usefulness → Sustainable Performance	0.026	0.013	1.943	Full Meditation effect
Circular Economy Practices → Leadership Competency → Sustainable Performance	0.092	0.040	2.321	Partial Meditation effect

5- Discussion on Results

H1: BDAC and SP, the beta coefficient (0.316), and the t-statistic level (3.989) representing the positive effect are significant. The literature review by scholars also discovered that organizations' operational efficiency and environmental sustainability performance have a positive relationship, as big data reporting enhances the quality of work processes [67]. Some pointed out that resource optimization and waste reduction strategies for sustainability depend on firms' data-driven insights. It stresses the capacity of big data analytics to change and agility in supply chain management, leading to sustainable business practices [68]. Our results show that firms with advanced analytics capabilities are more likely to be able to address their operations with the dimension than other stakeholders. Big data analytics led to sustainable manufacturing practices [69]. Data analytics is a broader term; in this study, the researcher has examined the firm's use of data analytics tools to achieve better sustainability objectives by making improved data-driven decisions.

H2: BDAC has the strongest direct impact on EPU with a beta value of 0.702 and t-statistic = 14.208. As seen, firms using advanced analytics have improved ratings of employee engagement and the perceived effectiveness of analytic tools. This also identified that data-driven processes are being increasingly utilized in organizations, and the research study showed that this helps employees make informed decisions [70]. Past studies reported that big data analytics aroused the expectation of information value among employees and thus improved operational efficiency [71]. Their research showed that employees would be more interested in using analytics tools if they could experience concrete benefits by performing them. A past study revealed that integrating big data analytics within workflows will boost employees' confidence in decision-making [72]. As employees see value in an analytics tool, it helps to create a data-driven decision environment.

H3: The results of the analytical part display a considerably large influence of BDAC on creating a DDC, with a beta coefficient = 0.750 and t-statistic = 27.574. It discovered that companies relying on big data analytics tend to build a solid data-driven culture [73]. Analytics alone does not make an organization more data-driven, their research showed. Instead, it refocused attention from technique to context: the extent to which companies that acted on advanced analytics actually reoriented strategist-implementer mindsets in response to new data sources. Further, it underscored the importance of culture in analytics and how a strong data-centric environment results from good alignment between why data is collected and business objectives [74]. Past studies also contend that developing a data-friendly culture of big data analytics in their processes is how they do it better [75]. They found that this integration improves decision-making and firm performance.

H4: showed a significant positive relationship between CEP and SP as illustrated by $\beta = 0.145$, $t=2.468$, which is also statistically significant. It is noted in past studies that shifting to the principles of a circular economy enables organizations to increase resource efficiency and waste reduction, which results in sustainable performance improvements [76]. These findings show how circular activity and its potential outcomes can translate to long-term value creation. Similarly, past studies have argued that the conscious investments to pass from these businesses to a circular economic model have positively influenced their environmental performance [77]. The study suggests these tactics could increase water-use efficiency and have less negative environmental impact. In addition to this, past studies have also suggested that efforts to foster a circular economy are sustainable and contribute to improving a competitive advantage [78]. In fact, their research reveals a strong association between circular practices and sustainability-related organizational performance metrics.

H5: The results showed a positive relationship between CEP and EPU, $\beta = 0.145$; t=2.793. Organizations following circular economy strategies are found to have a better level of employee engagement and satisfaction, according to Moktadir et al. [78]. The research revealed that employees "found their jobs more meaningful and less stressful and perceived their organization as committed to sustainability" when they witnessed the latter commitments. CEP provides a mechanism to make tools and related processes more valuable in employees' eyes by framing these artifacts within a supportable, sustainable structure; however, Tong et al. claimed that employees work better if they feel their actions contribute to large-scale environmental objectives [79]. Past studies confirmed that sustainable practices, including circular economy initiatives, positively contribute to employees' evaluations of their work being relevant. This study shows they can help create a sense of direction and relevance among employees [80].

H6: The analysis revealed a significant positive effect of CEP on LC ($\beta = 0.689$, t = 21.786). During this integrated, scholarly program, the students learn that leaders in circular economy organizations are more likely to hone and deploy their strategic thinking skills and problem-solving capabilities. This follows research demonstrating that involvement in sustainability initiatives results in a leadership style that is more adaptable and future-oriented [81]. It was observed that involvement in circular economy behaviors pushes leaders to build collaborative and stakeholder engagement skills necessary to lead sustainable change [81]. A past study confirmed that leaders embracing circular economy principles are more positioned to stimulate and inspire their teams, enhancing organizational performance [82]. This research showed a direct connection between sustainable actions and better leadership skills. Controversially, it suggested that while there are undisputed ways in which circular economy initiatives can embody leadership development, management largely depends on an embedded organizational culture and the prevailing leadership democratic style.

H7: There is a significant positive relationship between EPU and SP (0.177, t=2.632). The study by Molino et al. [83] stated that the perceived usefulness and its attributes to individual employees determine their engagement and performance. Their research showed that employees who value tools perform better for the organization, especially regarding sustainability work. A correlation between employee-perceived usefulness and sustainable performance metrics in organizations was established by Mio et al. [84]. Performance benchmarks by Jahanshahi et al. confirmed a connection between the efficacy of the tool's employees' use and their engagement in corporate sustainability goals. Evidence for the positive impact of perceived sustainability practices and tools as facilitators of sustainable performance through commitment to sustainability initiatives among employees has been reported by previous research [85].

H8: The analysis results support a direct positive relationship between DDC and SP with the β-coefficient of 0.120, t-statistics = 2.469. Earlier work reported that a data-driven culture helped organizations implement sustainability [24]. Their research showed that improvements in environmental sustainability could be better assessed through decision-making processes enabled by data analytics capabilities. That was part of the data-driven innovation that can be achieved from this kind of performance to sustainable performance. The challenge results simply showed that organizations deploying data smarter are better positioned to achieve their sustainability goals. This indicates that organizations can achieve improved ecological and economic performance with a strong data-driven culture [86]. The study demonstrated how sustainability could be intertwined with data-driven methods.

H9: Through the data analysis, we concluded that LC positively impacts SP t statistic value = 2.330 with a beta coefficient of significant negative -0.134. It has shown that the higher the leader's competencies in sustainability, the more effective the sustainability strategies will be. Their research revealed that leadership is the major driving force in framing sustainability from one organizational/cultural perspective to another level of priority [87]. Similarly, Sun et al. [88] focused on the relationship between transformational leadership styles regarding high competency and sustainability performance. The authors found that impactful leaders positively drive their teams towards sustainability objectives. This is supported by several researchers who found that leadership competency positively impacts an organization's sustainability performance through employee engagement and dedication to sustainability initiatives [89]. Their results showed that leadership is crucial in contributing to sustainable results.

H10: The $\beta=0.124$ t=2.564 indirect effect of BDAC on SP through EPU is significant in the size table. When tools were considered useful, organizations with high levels of big data capabilities managed better sustainability outcomes [90]. The study was conducted on the impact of big data analytics on employee engagement. It was verified that perceived usefulness significantly mediates the relationship between big data analytics and sustainable performance. The research concluded that employees who find analytics tools helpful could make better decisions and drive improved sustainability practices. Past studies also evidenced that by having employees who shared a positive perception of big data analytics, the integration of sustainable practices appeared to be facilitated, leading organizations to perform better according to their sustainability metrics [91]. It is demonstrated in this study that EPU and DDC are vital intermediates for enhancing the impact of BDAC and CEP on SP. In particular, EPU involves the beliefs held by employees about the value and effectiveness of big data tools in their day-to-day work, which in turn helps employees become more committed to using the big data tools for achieving improved outcomes. In EPU, these critical components were found to be factors, such as training and perceived ease of use, significantly affecting how employees use data analytics. Employees who believe they are well-trained and properly supported in using big data tools are more likely to find them useful. Hence, their contribution towards sustainable performance is greater.

H11: A modest indirect impact of CEP on SP through EPU, with about 0.026 as the beta coefficient and 1.943 as the t-statistic according to the analysis conducted and highlighted its employee's desire to access a circular economy practice, which positively correlates with the impact of sustainable commitment. Using this case study, their research demonstrated that an additional dimension of perceived usefulness could lead to more effective sustainability initiatives. Similarly, past research concluded that when employees perceive circular economy practices as useful to their commitments to sustainability agendas, they will result in superior sustainable tactics and enhance firm performance [92]. The authors highlighted how sustainable practices arise per employee perception in their research. A recent study highlighted that the perceived usefulness of sustainability initiatives, including circular economy practices, is positively associated with employee engagement, increasing sustainable performance. Their evidence reaffirms the need to influence employee perceptions positively [93].

H12: The analysis exhibits a significant indirect effect of BDAC on SP by a mediator, DDC, with value ß = 0.090 and t- statistic= 2.425. Past research showed that the presence of big data capabilities led organizations to substantially improve their sustainability performance, particularly for those with a strong data-driven culture [94]. They pointed to the interaction of data use and organizational culture in their study. A data-driven culture, confirmed by [95], is vital when using big data analytics to maximize innovation and sustainability performance. This study highlighted that by leveraging data to change customer behavior, one could maximize their use of analytics but cannot fully understand how the behavioral changes are more conducive to this understanding due to cultural forces. Similarly, another past study argued that organizations with a data-driven culture can exploit big data analytics capabilities more effectively, ultimately resulting in improved decision-making and sustainable performance development [96].

The philosophy around DDC is that data is king, or put differently, data is employed in decision-making processes. This cultural element was shown to mix with BDAC and CEP to create an atmosphere that makes data-driven insights valued and a major part of the organization's strategy. We identify specific factors within DDC that have had particularly strong effects on SP, including leadership support for data initiatives and collaborative data practice. Organizations that promote a data-driven mindset strategically tend to realize better performance outcomes as employees are trained to exploit data proactively.

Finally, a significant indirect effect is found, representing the influence of CEP on SP through LC ($\beta = 0.092$, t-Statistic =2.321). It also was identified that strong leadership is required to carry out circular economy practices [97] successfully. They demonstrated that leadership competencies contribute to enabling the adoption of sustainable practices and, eventually, performance enhancement of the organization. The study revealed that leaders proficient in addressing circular economy initiatives could heavily impact employee engagement and sustainability commitment levels, affecting overall performance outcomes [98].

6- Conclusion

By employing a quantitative research method based on positivism, this study offers insights into the relationships between BDAC, CEP, EPU, DDC, and LC on the SP of small and medium enterprises (SMEs) in Pakistan. Results revealed meaningful direct impacts of BDAC, CEP, EPU, DDC, and LC on SP. Moreover, empirically, CEP has a positive effect on SP from an organization's perspective and the EPU, as well as confirming interventions that respond to LC. In turn, the results revealed a set of partial mediation effects of EPU and DDC that mediate relationships between BDAC and SP, as well as CEP and SP, within the framework of relational design. The results of the present investigation demonstrated that efforts are needed to build a DDC and enhance utility perceptions among employees to harness a circular economy implementation mechanism to maximize SP. In sum, it improves the existing literature by providing empirical findings that stress the relationship between these factors and offers a roadmap for SMEs seeking to capitalize on sustainable growth in an increasingly competitive environment.

Despite the contributions of this study regarding the association between BDAC, CEP, EPU, and LC on SP in SMEs. There are a number of limitations. Initially, the study identifies only Pakistani SMEs as a topic of specific interest, which may restrain its broad applicability to other countries or large enterprises. It noted Pakistan's unique economic, cultural, and regulatory background and global implications. Furthermore, cross-sectional research designs just collect data at one point in time, which limits how much can be conditional about causality in addition to gathering perceptions and practices only as they exist at a certain moment; longitudinal studies could give a better account of the situation. There could be biases associated with using self-reports through questionnaires as they rely on self-report information that might introduce social desirability or response bias in our findings.

7- Declarations

7-1- Author Contributions

Conceptualization, F.E., M.B.H., and A.N.; methodology S.A., S.E., and M.B.H.; software, M.B.H., S.E., and A.N.; validation, M.B.H.; formal analysis, F.E. and S.E.; investigation, F.E. and J.A.E.; resources, J.A.E., F.E., and M.B.H.; data curation, J.A.E., A.N., and S.E.; writing—original draft preparation, F.E. and A.N.; writing—review and editing, M.B.H., F.E., and J.A.E.; visualization, A.N., S.A., and J.A.E.; supervision, M.B.H.; project administration, F.E. and SE. All authors have read and agreed to the published version of the manuscript.

7-2- Data Availability Statement

The data presented in this study are available on request from the corresponding author.

7-3- Funding

The authors received no financial support for the research, authorship, and/or publication of this article.

7-4- Institutional Review Board Statement

Not applicable.

7-5- Informed Consent Statement

All Participants involved in this research were informed about their consent to their participation in this research.

7-6- Conflicts of Interest

The authors declare that there is no conflict of interest regarding the publication of this manuscript. In addition, the ethical issues, including plagiarism, informed consent, misconduct, data fabrication and/or falsification, double publication and/or submission, and redundancies have been completely observed by the authors.

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