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Transforming Supply Chains: Powering Circular Economy with Analytics, Integration and Flexibility Using Dual Theory and Deep Learning with PLS-SEM-ANN Analysis

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Abstract: The Sustainable Development Goals and circular economy are two critical aspects of the 2030 Agenda for Sustainable Development. They both seek to reduce the waste of natural resources and enhance society's social, economic, and environmental goals. This study aims to identify, develop, test, and verify the significant antecedents that affect the adoption of supply chain analytics and its consequences for achieving the circular economy. We have divided the conceptual framework into two parts. In the first part, the relationship among data integration and scalability, organizational readiness, and policies and regulations as Technological–Organizational–Environmental factors as antecedents in adopting supply chain analytics. In the second part, the dynamic capabilities view grounded the relationship among supply chain analytics, supply chain integration, and sustainable supply chain flexibility effect directly and indirectly on the circular economy. Data have been collected using the survey method from 231 respondents from the manufacturing industry in Pakistan. Data have been analyzed using (i) partial least square structure equation modeling (ii) and artificial neural network approaches. The empirical findings proved that antecedents (data integrity and scalability, organizational readiness, and policy and regulation) and consequences (supply chain integration and sustainable supply chain flexibility) of supply chain analytics adoption would improve the circular economy performance. Additionally, artificial neural networks have supported these relationships. The adoption of supply chain analytics will enable organizations to supply chain integration. Additionally, organizations with more integration and analytics in their operations tend to have more flexibility and a circular economy. Moreover, organizations and society will obtain social, economic, and environmental benefits and reduce wastage and negative environmental impacts.

Keywords: supply chain analytics adoption; supply chain integration; sustainable supply chain flexibility; environment dynamics; circular economy; Technology–Organization–Environment (TOE); dynamic capabilities view; artificial neural networks; partial least square structure equation modeling

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1. Introduction

Wasting of natural resources has become a severe problem worldwide; people have destroyed more than two billion tons of resources, which are 60% more than the actual resources the earth can produce yearly, indicating we need three earth resources in 2050 [1,2]. The European Union alone produced 2.5 billion tons of waste in 2016, a considerable loss in natural resources that reveals the massive destruction of resources [3]. SDGs have focused on saving natural resources, and our society must shift from a "take-make-waste" paradigm to an "environment-friendly, carbon-neutral, and sustainable economy" [4].

Circular economy (CE) helped the researchers to find the solution to reduce wastage, pollution, biodiversity, and environmental challenges and regenerate natural resources [5]. Moreover, organizations like Philips have implemented the Sustainable Development Goals (SDGs no 7, 9, 12, 13, and 17) and become strategic partners with the Ellen McArthur Foundation to exercise sustainable practices for the betterment of society [6]. Fascinatingly, all the SGDs have focused on three main pillars (i) social, (ii) economic, (iii) and environmental. Additionally, CE and SDGs work together to achieve all three pillars of SDGs [5]. A well-established connection between digitization and CE has been evidenced by previous research [7,8]. Furthermore, the relationship between the Internet of Things and CE [9], as well as big data perspectives in terms of open government data [10], diffusion patterns [11], and predictive analytics [12], has been explored. Furthermore, previous research has explored the relationship between big data and CE in the supply chain [13], artificial intelligence and CE in reverse logistics [14], industry 4.0 and CE [15], and the intersection of supply chain analytics and CE [15]. Although there is a significant body of literature on big data analytics, more research is needed in supply chain analytics in the context of CE. Despite this distinction, the analytical processes and techniques share similarities, suggesting potential interchangeability between big data and supply chain analytics.

Organizational, environmental, social, and supply chain practices affect big data analytics to gain sustainable supply chain performance [16]. The use of big data analytics in the supply chain [17]. Moreover, the technological–organizational–environmental (TOE) factors affect the use of big data analytics to create corporate value from a dynamic capabilities perspective [18]; technological, organizational, and competitive pressure to adopt big data analytics in the supply chain in Saudi Arabia [19]; and technological, organizational, and environmental factor effects on supply chain analytics adoption (SCAA) for achieving operational performance and competitive advantage was found in the literature [20].

Data integrity, organizational readiness, and policy and regulations are critical factors in adopting supply chain analytics [20]. Data integrity ensures the accuracy and reliability of data, motivating organizations to prioritize data quality enhancements. Organizational readiness encompasses the willingness of individuals to embrace new technologies and processes, fostering a culture of adaptability and skill development. Policies and regulations impose obligations on organizations to protect data and maintain privacy, requiring them to navigate legal and compliance frameworks [20]. These factors, collectively representing technological, organizational, and environmental aspects, play pivotal roles in driving the successful adoption of supply chain analytics [20].

There are numerous and different TOE factors affecting big data analytics, and it is rare to find research on SCAA. There are also inconsistencies among these factors in the adoption of analytics, which raises the following research question.

RQ1. How do TOE factors, data integrity and scalability (technological factor), organizational readiness (organization factor), and policy and regulation (environmental factor) affect supply chain analytical adoption?

Environmental dynamism (ED) measures the change occurring in the external environment. Previous studies have explored the relationship between ED and supply chain integration (SCI), hostility, and financial performance [21]. ED and environmental hostility have been considered moderated variables [21], munificence, dynamism, hostility, heterogeneity as independent, integration as mediator and performance [22], SCI, supply chain dynamism, and logistics performance [23]; additionally, studies have explored the roles of big data analytics, supply chain ambidexterity, ED and performance [24]. However, the literature reveals inconsistencies and variations in the types of variables considered from different perspectives. Therefore, aligning and defining the ED within the context of SCAA and SCI to achieve CE goals is crucial.

ED has been shown to directly impact supply chain flexibility [25]. It has been considered an independent variable in the relationship between big data characteristics, supply chain agility, and performance [26]. Furthermore, ED affects digital supply chain platforms and environmental and economic performance in the context of Industry 4.0 [27]. Additionally, it serves as an independent variable between human, organizational, and technological factors and Industry 4.0 [28]. The literature has also explored the roles of big data analytics, supply chain ambidexterity, ED, and performance [24]. The moderated effects of industry dynamism between data analytical capabilities and sustainable supply chain flexibility (SSCF) were found in the literature [5]. However, there are missing links between ED and SCI, ED and SSCF were found, and there is an inconsistency in the supply chain literature regarding the association between ED and supply chain flexibility. Additionally, more literature must be explored to explore the relationship between ED and SSCF. To address this gap, our study aims to investigate and strengthen this relationship, giving rise to the following research question.

RQ2. Does environmental dynamism play a vital role in supply chain integration and sustainable supply chain flexibility?

It has been shown that big data analysis capability directly affects supply chain visibility and supply chain integration [29]. The relationship between supply chain integration and big data analytics [30]. The relationship among big data supply chain analytics, supply chain integration, and supply chain performance was found in the previous literature [31]. Moreover, the relationship between supply chain analytics and operational performance using resource-based theory [29] and supply chain analytics on operational supply chain transparency was found in the previous literature [32].

Big data analytical capabilities have direct effects on CE practices, supply chain management capabilities, sustainable performances [33], big data analytical capabilities, innovation, green supply chain performances [34], Industry 4.0 technologies, supply chain integration, CE [35], Industry 4.0 technologies have an effect on CE in the logistics industry [33], supply chain analytics adoption, and organizational performance were found in the previous literature [20].

Data analytics capabilities, sustainable supply chain flexibility, and CE were found in the previous literature [5]. Still, there are missing links between supply chain analytics adoption and supply chain integration, supply chain analytics adoption and sustainable supply chain flexibility, and supply chain integration and sustainable supply chain flexibility. Inconsistency was found in the previous literature on the supply chain that needs to dig out the relationship among supply chain analytics adoption, supply chain integration, sustainable supply chain flexibility, and CE, which has guided filling the gap in the literature.

RQ3. Is there any association between supply chain analytical adoption, supply chain integration, sustainable supply chain flexibility, and circular economy?

This present study addresses the gap in the supply chain literature, as previous research has predominantly concentrated on big data analytics rather than supply chain analytics. Furthermore, an inconsistency exists regarding supply chain analytics adoption factors, suggesting the need for further investigation and understanding. Moreover, the consequences of supply chain factors in achieving the circular economy exhibit consistency and a need for integration with supply chain analytics. In addition, many studies have focused on resource-based theory, TOE, or dynamic capabilities theory, highlighting the importance of theoretical integration. Moreover, most studies have only focused on structure equation modeling and have yet to see the validation via the ANN method. By exploring these issues, our research aims to advance knowledge in the field of supply chain analytics and provide a more comprehensive understanding of the complex dynamics between supply chain factors, circular economy goals, and the theoretical framework and methodology.

This study aims to identify, develop, test, and verify the significant antecedents of the effect of the adoption of supply chain analytics and its consequences for achieving the goals in two steps to address these questions. In the first step, we identified the antecedents of TOE factors such as data integrity and scalability (DIS), organizational readiness (OR), and policy and regulations (PR) affecting SCAA; in the second step, we focused on the consequences (such as SCI, SSCF, CE, and ED) of SCAA. Then, we tested the proposed framework using cross-sectional data with a sample size of 231 from Pakistani manufacturing industries. Our findings have contributed to the existing literature in three different aspects. (i) We have focused on the dual theory of TOE and Dynamic Capabilities View (DCV), which has extended the theoretical perspective, (ii) and findings of essential factors that are affecting CE; (iii) we have used the dual approach, (i) partial least square-structure equation modeling (PLE-SEM), (ii) and artificial neural networks (ANN) to understand the variables relationships in the proposed framework.

We have outlined this paper in Section 2, which focuses on the theoretical lens, hypotheses, and conceptual framework development. Then, Section 3 focused on the methodology, primarily concentrating on measurement and data collection. Further, in Section 4, we analyzed the data and interpreted the results. In the end, we have elaborated on implications, conclusions, discussion, and future directions for further research.

2. Theoretical Foundations and Literature Review

2.1. Technology-Organization-Environment (TOE) Framework

Rocco DePietro, Edith Wiarda, and Mitchell Fleischer have developed the multi-perspective TOE framework [36]. As a theory at the organizational level, TOE is focused on the organization's innovation perspective to enable it to adopt and implement innovative methods and procedures [37]. The organizational aspect of technology adoption has been divided into three broad perspectives.

According to the technological perspective of an organization, it is possible to use internal and external technologies within organizations, which are available on the market but have yet to be used by organizations. Moreover, these technologies are either technological practices or hardware equipment that can bring innovation to organizations [37,38]. Additionally, it includes all the factors that are affecting either the adoption or implementation of advanced and innovative technologies in the organizations, e.g., relative advantage, compatibility, observability, availability, characteristics, complexity, trialability, observability, perceived usefulness, security concerns, data quality and integration, technology competence, expected risk, and expected direct and indirect benefits [37,39–46]. In this study, we have focused on DIS as a TOE technological factor in adopting SCA.

The organizational perspective has focused on the organizational characteristics and resources, e.g., top management support, firm size, entrepreneurial orientation, technological orientation, formal and informal linking structure, communication process, slack, information intensity, employee knowledge, absorptive capability, organizational readiness, training and education, and technological and financial readiness [37,39–46]. We have focused on organizational readiness as the organizational factor of the TOE framework for SCAA.

The environmental perspective is linked to the context and surroundings in which the organization operates. There are many environmental factors affecting the adoption of technological innovations, e.g., competitive pressure, perceived trend, government support, legal framework, industrial characteristics, market structure, technical support infrastructure, government regulations, external task environment, external support, business partner, consumer or customer pressure, trading partner pressure, industrial pressure, and legal pressure [37,39–46]. The environmental factor of PR in adopting SCAA has been considered in this study. All three perspectives of the TOE framework have constraints and provide opportunities for organizations to adopt and implement innovative technologies [38,47].

2.2. Dynamic Capabilities View (DCV)

Teece first introduced DCV in 1997 [48]; it is an extension of the resource-based view (RBV) [49]. RBV has focused on helping organizations achieve competitive heterogeneity based on their unique organizational resources and capabilities. These unique resources and capabilities are difficult to imitate, giving organizations a competitive advantage [49]. Scholars have argued that nothing is static in the organizational context, making this theory controversial [50]. This issue was resolved using DCV because it focused on the strategic resources and capabilities to adapt to the changing environmental conditions to gain a competitive advantage [50]. Thus, DCV builds, integrates, and reconfigures internal and external resources and capabilities in a dynamic environment [48].

DCV recommended that organizations learn from the highly uncertain environment and respond to the dynamic environment for better results [24,51–53]. Furthermore, organizational tangible and intangible resources have integrated and responded to the evolving market conditions [51,52,54]. Additionally, the DCV has two contributing pillars: (i) dynamic capabilities affect performance; (ii) DCV is more visible in cases of technological disruption [55]. This study considers SCAA, SCI, SSCF, and CE as dynamic capabilities to gain a competitive edge.

2.3. Circular Economy (CE)

CE has been defined as " A system focused on the scarcity of resources and reduction in wastage disposal"; the CE system is opposite to the traditional open-ended system with value-added, financial, environmental, and social benefits [56]. Moreover, CE is the industrial system focused on efficiently using natural resources, restoration, design, increasing renewable energy efficiency, and reducing system risks [57]. European Environmental Agency [58] has focused on the five following critical points of CE:

1. Focus on fewer input resources and minimized exploiting natural resources, like energy and material, as input and increased efficiency;
2. Encourage organizations to share renewable resources, primarily focused on converting non-renewable resources into renewable resources; organizations must consider the recycling process and move towards sustainability;
3. Must reduce the carbon footprint through fewer emissions in the complete material life cycle;
4. Minimize wastage through fewer materials losses and save natural resources;
5. Support to re-use the product, expansion in the product life cycle, and retain the product as long as possible.

There is a need to shift from a linear supply chain to a circular. But it takes work; it requires the efforts of all the supply chain actors to participate in their role in this shift. Each actor can only do it if everyone has limited resources and capabilities [59,60]. Moreover, the complete circle starts from the organization to the end user. The shift from the traditional business to an integrated eco-friendly system involves all the stages, from input to output [61,62]. The current literature on supply chain management has provided the sustainable and green business infrastructure that should have been included in traditional supply chains [35,63]. This study focused on the technological (TOE framework) and supply chain capabilities (SCI and SSCF) to move towards the CE.

3. Hypotheses and Conceptual Framework Development

3.1. Data Integrity and Scalability (DIS)

Data integrity is vital in adopting SCA as the technological factor. Integrity is data reliability and accuracy, enabling organizations to adopt a new system or innovation [20]. Moreover, data integrity helps organizations reduce data redundancy and inaccuracy issues. Consequently, data integrity will also dictate the data pre-processing activities like the identification of the correct data type. Data integrity will boost the SCA capabilities and visualization of data and provide operational insights to organizations [64].

Additionally, big data quality is essential to making managerial decisions [65]. Scalability has been considered from both the horizontal and vertical perspectives of data analytics. The scalability of data expended the operations, i.e., the breath, storage capacity, memory, and processing power [20]. Additionally, the association between DIS and SCAA was found in the previous literature [20], and the supply chain literature has provided the argument to develop the following hypothesis.

H1a. *DIS has a positive effect on SCAA.*

3.2. Organizational Readiness (OR)

OR is the organizational capability to accept information technology infrastructure and educate employees about innovative and modern technologies [66,67]. From the perspective of SCAA, organizations must be ready to invest in (i) tangible, e.g., data analytical equipment and system [68], and (ii) intangible, e.g., data sources, which are compulsory to be analyzed [69], and (iii) organizations must invest in the data mining tools and techniques to extract data from warehouse, and supply chain management system [64]. Moreover, data analytical skills and capabilities, e.g., such as simulation, programming, machine learning, and mathematics, are required to conduct data analytics efficiently [29,70], and top management support for adopting and implementing innovative technologies. Furthermore, the leadership commitment boosts the implementation of data-oriented processes and SCAA [29,70]. A positive association between OR and SCAA was found in the previous literature [20]. Based on the above arguments, the following hypothesis has been formulated.

H1b. *OR has a positive effect on SCAA.*

3.3. Policy and Regulation (PR)

Government regulations continuously pressure organizations to adopt advanced innovative technologies (Hsu et al., 2014), e.g., the General Data Protection Regulation and European Economic Area in the European Union have changed organizational data collection, processing, and privacy behavior [71]. But, organizations are facing problems implementing these laws because most organizations do not have structured data, and it is a big challenge for organizations for SCAA [72,73]. Additionally, government regulations pressure them to adopt the analytical system in their supply chains [74]. Furthermore, every country has its data privacy laws worldwide, which must be considered while conducting cross-border supply chain and logistic activities [75]. The global 205 national indicative policy initiative regarding data has focused on (i) how to make public data more accessible, (ii) how to share the data with the private sector, (iii) how to enable humans to do data analytics, and (iv) how to make data-driven national policies [76]. The direct relationship between PR and SCAA was found in the SCM literature [20]. Hence, we have developed the following hypothesis.

H1c. *PR has a positive effect on SCAA.*

3.4. Supply Chain Analytical Adoption (SCAA)

Big data analytics and supply chain analytics extract insights, correlations, and patterns from complex datasets. While big data analytics applies to various domains, supply chain analytics focuses explicitly on supply chain data, which indicates that supply chain analytics is more suitable in supply chain studies, both leveraging statistical tools and modeling techniques to enable data-driven decision making for organizations. Implementing advanced information technologies and systems enables organizations to make their processes more integrated, gain a competitive edge, and become efficient in improving organizational performance [12,77–80]. Supply chain scholars have focused on the SCA as the essential factor in gaining a competitive advantage [81–83]. Additionally, the effective implementation and use of SCAA will improve organizational internal and external processes, e.g., reduce stockouts, wastages, lead time, costs, and planning errors and improve quality control and material availability. All these factors will improve the supply chain, organization, and CE performance [72,84,85].

We have found the relationship between SCI and big data analytics from the perspective of the organizational processing theory [86], SCI and big data analytics from the perspective of data-driven decision culture [30], the exact SCI and big data analytics relationship for green innovation [87], artificial intelligence, SCI, big data analytics, and environmental performance [88]. Additionally, data analytical capability flourishes organizational flexibility [89], data analytics is the enabler for supply chain flexibility [90], and the relationship between SSCF and big data analytics was found from a manufacturing perspective while considering the CE [91]. Organizational engagement, alliance, and data analytical capabilities have been considered to gain SSCF to achieve CE performance [5]. Moreover, digital technologies' role in CE [92]. The relationship among business intelligence and analytics, data-driven insights, institutional pressures, data-driven decisions, data analytical capabilities, adoption of big data analytics, and CE performance was found [93,94]. As mentioned above, the literature enables us to draw the following hypotheses.

H2a. *SCAA has a positive effect on SCI.*

H2b. *SCAA has a positive effect on SSCF.*

H2c. *SCAA has a positive effect on CE.*

3.5. Environmental Dynamism (ED)

ED has based on two major factors (i) volatility and (ii) uncertainty. In organizations, volatility refers to the amount and rate of environmental change [95]. During the recent COVID-19 pandemic, the government put restrictions to control the spread of the virus [96], and the market structure, consumer behavior, and supply chain rapidly changed as a result of demand and market instability [97,98]. The change in the natural environment will not only change the organizational process. Technological disruption and the advent of advanced information technologies also bring change in the market and industry that will shift traditional approaches to more innovative ones. ED has been considered a moderator between big data analytics and supply chain ambidexterity [24]. The mediating effect of SCI between ED and firm performance [21,22], supply chain dynamism, has been considered a moderator between SCI and logistic performance [23]. The moderated relationship of industry dynamism was found between the adoption of big data analytical powered artificial intelligence and circular economy [94]. The moderated relationship of industry dynamism was found between data analytical capability and SSCF [5].

H3a. *ED has moderated the effect between SCAA and SCI.*

H3b. *ED has moderated the effect between SCAA and SSCF.*

3.6. Supply Chain Integration (SCI)

SCI is the collaboration among all stakeholders involved in value-added activities in the supply chain like warehouse management, purchasing, distribution, sales, information, and design [99,100]. Moreover, SCI streamlines organizational processes, sharing information and resources among supply chain activators to gain financial and operational performance [101]. SCI has been categorized as internal and external integrations [102]. Internal integration aligns the organizational departments like R&D, marketing, and operations with each other, so the more they are integrated, the higher SCI leads to higher performance in CE [103]. The external integration will lead to environmental planning and waste reduction in ecological activities to strengthen the CE [104]. The application of digital technologies has a relationship between supply chain collaboration, integration, and CE, indicating (i) a direct relationship between SCI and CE and (ii) mediating effect of CE between technological applications and CE [105]. The direct and positive relationship between SCI and CE was found in previous literature [35]. Additionally, industry 4.0 has changed the concepts of organizational processes via innovation. SCI mediates data processing technologies and CE [35].

H4a. *SCI has a positive effect on CE.*

H4b. *SCI has a mediating effect between SCAA and CE.*

3.7. Sustainable Supply Chain Flexibility (SSCF)

SSCF is becoming popular among supply chain scholars [5,106]. The sustainable supply chain is based on three main social, environmental, and economic pillars to accelerate organizational performance [107]. Additionally, the supply chain capabilities have three aspects (i) visibility (sensing), (ii) agility (seizing), (iii) and flexibility. The flexibility is the reconfiguration. Accordingly, the SSCF is the organizational reconfiguration capability to adjust its supply chain to achieve social, environmental, and economic benefits to gain a long-term competitive edge and performance [108]. Process level SSCF automates the core processes at sub-systems for logistics, material demand, green remanufacturing, auto data collection, transfer and exchange, operation simulation, equipment, recycling, market flexibility, and the unit of production to reduce costs and environmental impacts and increases competitive advantage and long term success [5,109,110]. Additionally, green practices and sustainable supply chains gained the attention of supply chain scholars [5,33,111,112], green motives, and green practices [113]; moreover, the relationship between SSCF and CE in the perspective of data analytics, alliance, and engagement capabilities has been focused [5]. Furthermore, the mediation of SSCF was found between data analytics and CE in the supply chain literature [5]. SCI is directly associated with supply chain flexibility and mediates between SCI and business performance in the presence of an innovation system and supply chain resilience [114]. Moreover, supply chain flexibility mediates SCI and supply chain performance [115]. The following hypotheses have been formulated in light of the above arguments.

H5a. *SSCF has a positive effect on CE.*

H5b. *SSCF has a mediating effect between SCAA and CE.*

H5c. *SSCF has a mediating effect between SCI and CE.*

The following conceptual framework has been developed in light of the literature review, theoretical foundation, and hypotheses, as shown in Figure 1.

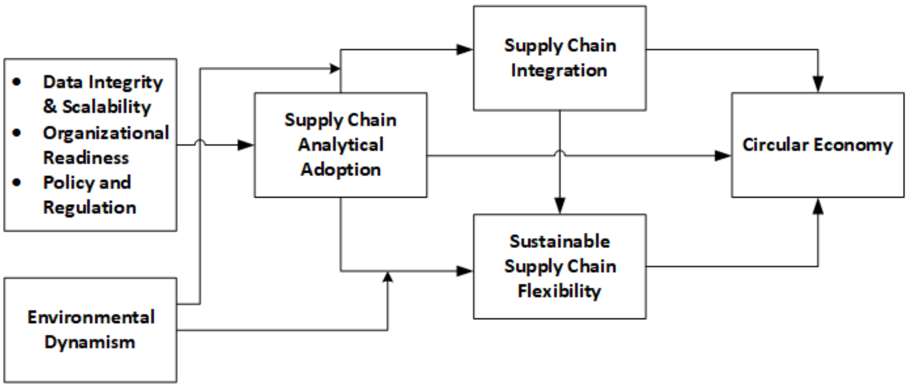

Figure 1. Conceptual framework.

4. Methodology

4.1. Measures

A five-point Likert Scale was used to assess all variables. Additionally, the questionnaire was evaluated by three academicians and professionals in the field of management information systems, supply chain, and psychology. The TOE framework is famous in the supply chain literature [116]. DIS is a technological factor measured using five items [20,46]. OR is organizational has six items [20,38,117], and PR is the environmental factor has three items [20,117].

The independent variable, SCAA, was measured using three items [20,116,118]. The mediating variable SSCF was measured using seven items [5,110], and SCI as mediator was measured using five items [35,102,119]. A moderated variable ED was also measured using four items in this current study [18,24]. Finally, the dependent variable CE was measured using four items [35,120–122]. All the items have mentioned in Appendix A.

4.2. Data Collection

We have investigated the TOE framework to adopt SCA and its impact on the SCI, SSCF, and CE. The conceptual framework has been tested in the Pakistani manufacturing industry. Surveys have been conducted to collect the data in this study, consistent with the previous literature [12,99]. Online questionnaires have been developed. Data have been collected using simple random sampling from December 2022 to January 2023. The respondents are volunteers and have not paid anything to the respondents. Data privacy has been kept and communicated during the data collection process. Only the aggregated results have been published and shared.

We distributed survey links among 473 respondents and received 268 responses. After that, we removed 37 responses, leaving 231 valid responses for further analysis. The sample size is sufficient to conduct further investigation. Scientifically calculating samples using G*Power software 3.1.9.7 is recommended in the literature [123]. The G*Power software has suggested that the sample size for this study should be 153, but this study has a sample size of 231, which is higher than the required sample size. The power is 0.950, and the significance is 5%. So, there is no sample size issue to conduct analysis. Most of the participants are male (134 respondents, 58.01%), have undergraduate education (152 respondents, 65.80%), 4–6 years of experience (107 respondents, 46.32%), occupational level of a supervisor (110 respondents, 47.62%), and belong to the electronics industry (94 respondents, 40.69%).

4.3. Common Method Bias (CMB)

CMB is a typical supply chain issue and has gained the attention of supply chain scholars [80,124]. The situation arises when data from dependent and independent variables are simultaneously taken from the same respondents. We have calculated CMB using the full collinearity method. Based on this method, all the variables in this study are considered independent variables, and a dummy random variable is used as the dependent variable. It is evident from the inner variance inflation factor (VIF) values that they are less than 3.3 [125]. There is no problem with CMB found in the current research.

4.4. Research Tools

We have used Smart PLS 3.3.9 for partial least square structural equation modeling (PLS-SEM) and SPSS 27 for artificial neural networks (ANN) analysis. Moreover, we have used Google Forms for the questionnaire design. EndNote X9 is used for references, and Microsoft Office 365 for data handling and report writing. Additionally, we have used the Grammarly Premium account to check the grammatical mistakes in the manuscript.

5. Results

5.1. Measurement Model

It is fundamental to understand that structural equation modeling (SEM) is based on measurements and structural models. An analysis of the measurement model has been carried out in terms of the reliability and validity of the data. Furthermore, the structural model has been analyzed using path coefficients R^2, F^2, and Q^2 [126].

5.2. Reliability

The first step of the SEM is to measure the reliability using Cronbach's Alpha (α) and Composite Reliability (CR) methods. The literature has suggested that the threshold values of both α and CR must be higher than 0.70 [126]. We have calculated the values of α and CR. The results are mentioned in Table 1. All the values are higher than the threshold values, indicating that all the variables are reliable.

Table 1. Measurement model.

Constructs	Factor Loadings	VIF
Data Integrity and Scalability (α = 0.800, CR = 0.861, AVE = 0.555)		
DIS1	0.728	1.610
DIS2	0.768	1.662
DIS3	0.820	1.731
DIS4	0.668	1.453
DIS5	0.735	1.475
Organizational Readiness (α = 0.867, CR = 0.900, AVE = 0.600)		
OR1	0.772	1.826
OR2	0.734	1.713
OR3	0.761	1.836
OR4	0.814	2.16
OR5	0.808	1.951
OR6	0.755	1.715
Policies and Regulations (α = 0.761, CR = 0.862, AVE = 0.677)		
PR1	0.786	1.427
PR2	0.849	1.663
PR3	0.832	1.595
Environmental Dynamism (α = 0.780, CR = 0.858, AVE = 0.602)		
ED1	0.762	1.553
ED2	0.780	1.524
ED3	0.775	1.542
ED4	0.787	1.551
Supply Chain Analytics Adoption (α = 0.719, CR = 0.843, AVE = 0.641)		
SCAA1	0.803	1.442
SCAA2	0.840	1.575
SCAA3	0.757	1.32
Supply Chain Integration (α = 0.855, CR = 0.896, AVE = 0.633)		
SCI1	0.830	2.030
SCI2	0.790	1.792
SCI3	0.770	1.702
SCI4	0.793	1.840
SCI5	0.795	1.863
Sustainable Supply Chain Flexibility (α = 0.874, CR = 0.903, AVE = 0.570)		
SSCF1	0.746	1.802
SSCF2	0.773	1.890
SSCF3	0.729	1.707
SSCF4	0.757	1.877
SSCF5	0.737	1.761
SSCF6	0.787	1.986
SSCF7	0.753	1.803
Circular Economy (α = 0.901, CR = 0.922, AVE = 0.627)		
CE1	0.811	2.281
CE2	0.778	1.916
CE3	0.79	2.072
CE4	0.804	2.172
CE5	0.791	2.103
CE6	0.813	2.179
CE7	0.753	1.809

5.3. Convergent Validity

Data validity has been tested using convergent validity (CV) and discriminant validity (DV). The CV indicates there is a theoretical relationship among the study variables. The convergent validity has been measured via the average variance extracted (AVE) and factor loading method. The threshold values for the AVE are recommended to be greater than 0.50, and the factor loading must be greater than 0.70 [126]. The results of both the AVE and factor loadings have been calculated and are shown in Table 1. Even though all the values are higher than the threshold values, this proves the convergent validity of the constructs.

5.4. Discriminant Validity

The theoretical difference among constructs can be found through discriminant validity. A criterion-based method in PLS-SEM has been developed using Fornell and Larcker criterion that measures DV [127]. According to this technique, the square root of AVE must be greater than the inter-correlations between the variables throughout the study [127]. Table 2 contains the Fornell and Larcker criterion values. Across all constructs, the values are above the cut-off values, indicating that the constructs have DV.

Table 2. Fornell and Larcker criterion method.

	1	2	3	4	5	6	7	8
1. CE	***0.792***							
2. DIS	0.581	***0.745***						
3. ED	0.633	0.364	***0.776***					
4. OR	0.715	0.543	0.530	***0.774***				
5. PR	0.578	0.602	0.389	0.514	***0.823***			
6. SCAA	0.618	0.573	0.530	0.587	0.611	***0.801***		
7. SCI	0.745	0.641	0.491	0.638	0.543	0.582	***0.796***	
8. SSCF	0.702	0.602	0.701	0.674	0.503	0.674	0.678	***0.755***

Bold and Italic diagonal, horizontal values are the square root of AVE.

Hetero-trait Mono-Trait (HTMT) is the most commonly used method to calculate DV in contemporary research [128]. In addition, the threshold value of HTMT must be less than 0.85 to be considered valid [128]. In Table 3, we have shown the values of the HTMT. According to the results, there is a DV to the constructs.

Table 3. HTMT.

	1	2	3	4	5	6	7	8
1. CE								
2. DIS	0.681							
3. ED	0.753	0.458						
4. OR	0.806	0.644	0.642					
5. PR	0.698	0.771	0.506	0.625				
6. SCAA	0.766	0.743	0.709	0.736	0.826			
7. SCI	0.848	0.781	0.596	0.739	0.674	0.74		
8. SSCF	0.789	0.713	0.846	0.771	0.614	0.848	0.785	

5.5. Structural Model

When we perform PLS-SEM, we calculate the structural model once the measurement model has been completed. This structural model is based on the hypotheses tested using path coefficients R^2, F^2, and Q^2 [126].

5.6. Hypotheses Testing

In PLS-SEM, automatic bootstrapping on 500 subsamples has been performed to test the hypotheses. The results supported all the hypotheses and were accepted. Moreover, the results showed a positive and significant influence of data integrity and scalability (β = 0.210; p = 0.012), organizational readiness (β = 0.304; p = 0.001), and policies and regulations (β = 0.328; p = 0.000) on supply chain analytical adoption, which supported H1a, H1b, and H1c. Additionally, the supply chain analytical adoption has a positive effect (β = 0.524; p = 0.000) on supply chain integration, (β = 0.357; p = 0.000) on sustainable supply chain flexibility, (β = 0.159; p = 0.000), and circular economy, which supported the H2a, H2b, and H2c. Furthermore, supply chain integration (β = 0.461; p = 0.000) and sustainable supply chain flexibility (β = 0.282; p = 0.015) affect the circular economy. Additionally, environmental dynamism's moderated effect with supply chain integration (β = 0.151; p = 0.017), and (β = 0.131; p = 0.018) sustainable supply chain flexibility, which supported the H3a and H3b. The results of direct hypotheses have been mentioned in Table 4.

Table 4. Direct hypotheses.

Hypotheses	B	T Values	*p* Values
DIS → SCAA	0.210	2.526	0.012
ED → SCI	0.333	3.697	0.000
ED → SSCF	0.476	5.803	0.000
Moderating Effect 1 → SCI	0.151	2.391	0.017
Moderating Effect 2 → SSCF	0.131	2.383	0.018
OR → SCAA	0.304	3.354	0.001
PR → SCAA	0.328	4.222	0.000
SCAA → CE	0.159	1.895	0.059
SCAA → SCI	0.524	7.332	0.000
SCAA → SSCF	0.357	4.504	0.000
SCI → CE	0.461	4.229	0.000
SCI → SSCF	0.289	3.509	0.000
SSCF → CE	0.282	2.433	0.015

The structural model of direct hypotheses having the direct path coefficients on each path, R^2 in the circle of each dependent variable, and factor loadings of each item have been mentioned between the variable and item paths in Figure 2.

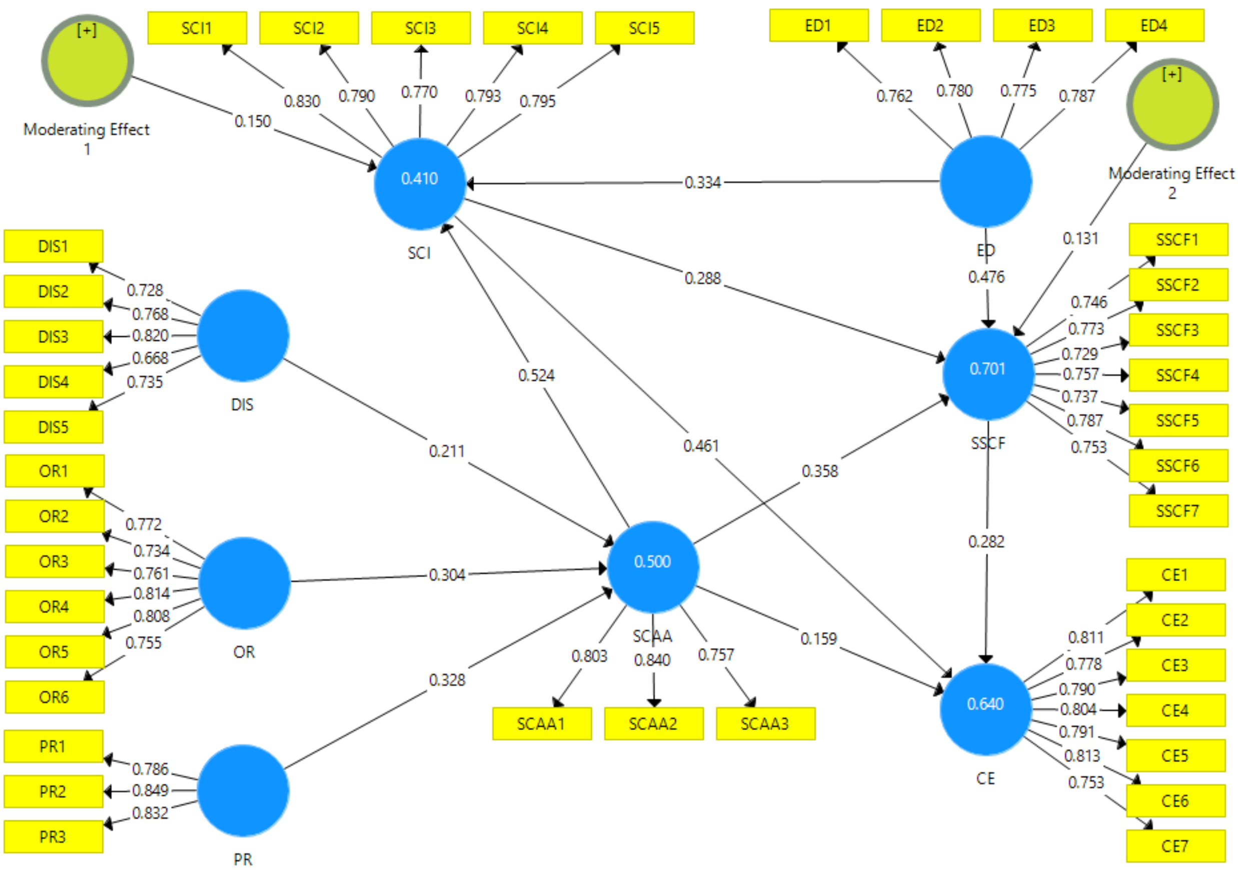

Figure 2. Path coefficients of circular economy.

5.7. Mediation Analysis

The mediation analysis has been conducted using PLS-SEM. This method uses direct, indirect, and total path coefficients to measure the variance accounting for (VAF) [129,130]. To calculate the mediation effects for our study, we used the same calculation method recommended in previous studies [129,130]. According to the VAF, the values of VAFs below 20, between the values of 20 and 80, and above the values of 80 indicated no mediation, partial mediation, and full mediation, respectively. The mediation results are outlined in Table 5.

Table 5. Mediation analysis.

Mediations	Direct β	Indirect β	Total β	VAF	Mediation Type
SCAA → SCI → CE	0.159	0.241	0.401	0.603	Partial Mediation
SCAA → SSCF → CE	0.159	0.101	0.260	0.388	Partial Mediation
SCI → SSCF → CE	0.461	0.081	0.542	0.150	No Mediation

5.8. Effect Size and Predictive Relevance

The model's effect size (F2) has been calculated based on PLS-SEM. Using the F^2 method, F^2 values ranged from 0.02, 0.15, to 0.35, respectively, indicating a low, medium, and high effect size level [131]. Additionally, if the value of Q^2 is greater than zero, it indicates predictive relevance; if the value is 0.25, it indicates medium predictive relevance; and if it is greater than 0.50, it indicates a much higher predictive relevance [126]. Taking into consideration both F^2 as well as Q^2, the results favor this study, as shown in Table 6.

Table 6. Effect size and predictive relevance.

Endogenous Variables	R^2	Q^2	Exogenous Variables	F^2
Supply Chain Analytical Adoption	0.5	0.305	Data Integrity and Scalability	0.05
			Organizational Readiness	0.12
			Policy and Regulation	0.126
Supply Chain Integration	0.41	0.247	Supply Chain Analytical Adoption	0.286
			Environmental Dynamism	0.114
Sustainable Supply Chain Flexibility	0.701	0.384	Supply Chain Integration	0.164
			Supply Chain Analytical Adoption	0.205
			Environmental Dynamism	0.411
Circular Economy	0.64	0.395	Sustainable Supply Chain Flexibility	0.093
			Supply Chain Integration	0.301
			Supply Chain Analytical Adoption	0.036

5.9. Model Fit

It measures how well the data fit the proposed model, often called the goodness of fit (GoF). The GoF was calculated by calculating the root of the under root of AVE*R^2 [130,132,133]. GoF analyses show that the results favor GoF [130,132,133]. In addition to using the Normed Fit Index (NFI), another method of analyzing the fit of the PLS-SEM model was employed to determine whether it was a good fit. The closer the value is to 1, the better the fit. Moreover, when the model's standard root mean square (SRMR) approaches zero, the model is more likely to be well fitted [130,134,135]. Table 7 shows the results of the GoF and PLS-SEM-Model fits in the table below.

Table 7. Goodness of fit.

Constructs	AVE	R Square
CE	0.627	0.640
SCAA	0.641	0.500
SCI	0.633	0.410
SSCF	0.570	0.701
	0.618	0.56275
Goodness of Fit		0.585

Note: Smart PLS model fit values are SRMR = 0.059 and NFI = 0.717.

5.10. Artificial Neural Network (ANN)

We have employed the ANN approach to check the robustness. Because the ANN approach can predict model accuracy and non-linear relationships from complex data sets, we have used the "multilayer perceptron" MLP to analyze the data in this study. The MLP approach is based on three layers, i.e., input, hidden, and output layers. Moreover, the dependent variable was considered as the output, the complexity of the problem is directly proportional to the values of hidden layers [136], and covariates as input layers. Our proposed model is complex; we have divided this study into sub-steps as the previous literature recommended [137]. In the first step, we employed the SCAA predictors (DIS, OR, and PR) and SCI predictors (SCAA and ED) in the second step. The third step includes SSCF predictors (SCAA, ED, and SCI); the fourth step comprises CE predictors (DIS, OR, PR, SCAA, ED, SCI, and SSCF) as input. With 70% of the data, the model was trained, and 30% of the data were used to test the model. We have also reduced the model over-fitting by employing ten-fold cross-validation [138].

It has been found that Root Mean Square Error (RMSE) is a good indicator for predicting the accuracy of the model. The average RMSE for CE training data has a value of 0.111, and testing data has 0.114, which shows no significant difference between the training and testing data, indicating high precision [139,140]. Additionally, models 1, 2, and 3 have been calculated separately. The values of RMSE of all the models have been mentioned in Table 8.

Table 8. Artificial neural networks.

Neural Network	Model 1		Model 2		Model 3		Model 4	
	Input Covariates:		Input Covariates:		Input Covariates:		Input Covariates:	
	DIS, OR, PR		SCAA, ED		SCAA, ED, SCI		DIS, OR, PR, SCAA, ED, SSCF, SCI	
	Output: SCAA		Output: SCI		Output: SSCF		Output: CE	
	Training	Test	Training	Test	Training	Test	Training	Test
ANN1	0.111	0.107	0.138	0.164	0.105	0.093	0.113	0.119
ANN2	0.112	0.117	0.152	0.128	0.090	0.120	0.116	0.109
ANN3	0.121	0.097	0.152	0.133	0.099	0.100	0.105	0.108
ANN4	0.111	0.115	0.144	0.181	0.106	0.104	0.102	0.116
ANN5	0.116	0.091	0.144	0.150	0.105	0.113	0.120	0.101
ANN6	0.110	0.114	0.138	0.148	0.091	0.120	0.119	0.112
ANN7	0.105	0.113	0.155	0.125	0.104	0.096	0.097	0.138
ANN8	0.115	0.105	0.155	0.130	0.096	0.111	0.108	0.132
ANN9	0.112	0.111	0.148	0.141	0.111	0.071	0.108	0.126
ANN10	0.114	0.106	0.138	0.166	0.097	0.103	0.123	0.080
Average	0.113	0.108	0.146	0.147	0.100	0.103	0.111	0.114

5.11. Sensitivity Analysis

The sensitivity analysis was calculated using the output values of the independent variable's importance by taking the average and then dividing the highest value by each construct of ten networks [138,140,141]. The results of the sensitivity analysis are in line with the results of the SEM analysis. The most critical factor for SCAA in SEM is PR ($\beta = 0.328$), SCAA showed the highest value for SCI ($\beta = 0.524$), SSCF was found to be ED ($\beta = 0.476$), and SCI ($\beta = 0.461$) found the most significant factor for CE. All these SEM results are consistent with the normalized importance percentage, as shown in Table 9.

Table 9. Normalized importance percentage.

Predictor	Model 1	Model 2	Model 3	Model 4
	Input Covariates:	Input Covariates:	Input Covariates:	Input Covariates:
	DIS, OR, PR	SCAA, ED	SCAA, ED, SCI	DIS, OR, PR, SCAA, ED, SSCF, SCI
	Output: SCAA	Output: SCI	Output: SSCF	Output: CE
DIS	74.63			33.3
OR	76.55			99.47
PR	100			46.23
SCAA		100	79.66	35.45
ED		83.8	100	86.36
SCI			60.73	100
SSCF				54.82

6. Discussion

The H1a,b,c results have developed the relationship among TOE factors of DIS, OR, and PR with SCAA; all the results favor the hypotheses and were accepted. These results are aligned with the previous literature [20]. This indicates where the data integrity is high. Organizations are ready to adopt the new technology. Government policies and regulations put pressure on organizations that favor implementing supply chain analytics technologies in their organizations.

Additionally, the H2a,b,c results have focused on SCAA and its impact on SCI, which shows the positive effect supported by the previous literature [88]. In addition, there is evidence of a relationship between data analytics and SSCF in the literature [5,91]. In addition, the increasing integration of digital technologies into CE provides a logic for SCAA to positively impact CE [92], which is further supported by the relationship between data analytical capabilities and CE [93]. The results proved that the successful adoption and implementation of SCAA will increase the SCI, SSCF, and CE. Organizations that use their SCAA more efficiently have higher chances of integration, flexibility, and CE performance.

The third hypothesis results showed that H3a,b indicate ED has moderated the relationship between SCAA and SCI, which was not found in the literature. But ED found a common moderated variable in supply chain the literature. Additionally, the moderated relationship of ED between SCAA and SSCF was logically supported through the previous supply chain literature that has developed the industry dynamism as a moderated variable between data analytics and SSCF [5]. ED moderates both SCI and SSCF with SCAA.

The results of H4a,b have demonstrated the direct effect of SCI on CE, supported by previous literature [35,105]. Organizations with more integration with their suppliers, customers, and internal processes have a higher success rate in CE performance because every stakeholder has the same goal to protect the environment and gain social and economic benefits. Further logical support for the mediating role of SCI between SCAA and CE can be found in the previous literature that has examined the mediating effect of SCI between data processing technologies, digital technology applications, and CI [35,105]. It was accepted that the use of advanced information technologies like SCAA enhances the SCI, and in the same way, it will enhance the CE directly and indirectly.

The last hypothesis H5a,b,c is related to SSCF. The SSCF directly affects CE, which was supported by the previous literature [5]. Moreover, the mediating effect of SSCF between SCAA and CE was not found in the literature. However, the logic has been developed that SSCF mediates between data analytics and CE, which is aligned with the supply chain study [5]. The mediating effect of SSCF between SCI and CE was also missed in the literature. It has been found that the relationship between supply chain flexibility and supply chain and business performance that mediates between SCI and supply chain and business performance is supported by the literature [114,115]. The results favor the proposed hypotheses and highlight the importance of SSCF for SCI and SCAA for CE.

This study has played a role in carbon foot reduction. Because supply chain operations will be handled on computer-based applications to analyze the data instead of taking prints. Additionally, government rules and regulations are also putting restrictions on low carbon emissions. Furthermore, integration and flexibility in supply chain operations will also improve the supply chain operations, increasing sustainability and enhancing the circular economy. The objectives of this study are aligned with SDGs and sustainable operations.

7. Conclusions and Implications

Supply chain analytical capabilities refer to the unique abilities of employees to understand and optimize their supply chain activities by reducing their carbon footprints. This study developed a comprehensive framework using the TOE model and dynamic capabilities theory to collect data from 231 respondents across various business sectors in Pakistan. Our study sought to answer three research questions and test thirteen hypotheses, including sub-hypotheses, all of which were supported by the results. The results revealed that adopting SCA positively influences SCI, SSCF, and CE. Additionally, this study found that SCI significantly affects SSCF and CE. Furthermore, the moderated effects of ED were found to be positive between SCI and SSCF with SCAA. The robustness of our findings was further supported by the ANN approach, which yielded favorable results for the proposed hypotheses.

7.1. Theoretical Implications

It has been explained in the literature how the theoretical contribution is made [142]. Three different aspects of this study contribute to the theory in different ways. First, the theoretical implications of this study stem from integrating two fundamental theories, namely the TOE and DCV theories. While the previous literature has predominantly focused on either TOE or DCV in the context of adopting new technologies, our study contributes by incorporating both theories [44,53]. Second, we have addressed the missing links of SCAA, SCI, SSCF, and CE. Third, by employing PLS-SEM and ANN methods, we offer a dual approach that extends beyond the predominant use of PLS-SEM in existing literature [5,35].

7.2. Practical Implications

From a practical standpoint, our study has important implications for organizations. It highlights the significance of implementing supply chain analytics to integrate processes and stakeholders, ultimately enhancing operational flexibility. Furthermore, adopting supply chain analytics enables organizations to reduce their carbon footprints and transition towards a circular economy, thereby attaining economic, social, and environmental benefits that foster competitive advantage in a dynamic business environment.

7.3. Social Implications

The social implications of this study are significant, as it contributes to reducing natural resource waste and promoting a greener environment. Moreover, the research encourages the conversation of resources for future generations and cost reduction. By aligning with the Sustainable Development Goals and international standards, this study aims to protect the environment for the betterment of individuals, organizations, and society.

7.4. Limitations and Future Research Direction

We have attempted to use a rigorous research approach. But, still, there were certain limitations found during the research. These limitations can be considered in future studies. First, we have used the convenience sampling method, which has some limitations. In future studies, researchers can use other types of sampling that align with their research objectives. Second, in this study, we have tried to find sufficient variance in the model. Still, in the future, different theories and uninvestigated variables can be used to find our study's new lens. Third, the various research approaches, like focus groups and interviews, will help the researchers investigate the other significant factors contributing to the existing framework. Fourth, we have only focused on the Pakistani manufacturing industries. The same framework can be tested in developing countries like India and China and in developed countries like Germany and the USA. Additionally, the conceptual framework can be tested in multiple industries for generalization.

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Conflicts of Interest: The authors declare no conflict of interest.

Appendix A

Data Integrity and Scalability

- The utilized supply chain analytics systems are compatible with the company's existing hardware and software applications.
- Data quality issues are relevant to my organization when implementing supply chain analytics systems.
- Data interoperability issues are relevant to my organization when implementing supply chain analytics systems.
- supply chain analytics systems are supported by data quality and data integration tools.
- Customer data needs to be integrated into supply chain analytics systems and checked for quality.

Organizational readiness

- Our organization has the human capabilities and capacity on using supply chain analytics systems to support operations.
- Our organization has no difficulties in accessing all the necessary resources (e.g., funding, people, time) to adopt supply chain analytics technologies.
- Our organization employees are knowledgeable and skillful in supply chain analytics systems.
- Our organization supports ongoing personnel training schemes on supply chain analytics systems.
- The company management considers supply chain analytics systems important and supports their use.
- The management is willing to communicate with staff and participate in the implementation process of supply chain analytics systems.

Policy and Regulations

- There is legal protection in the use of supply chain analytics systems, but companies have difficulty complying with policies and regulations due to the large amount of unstructured data.
- Legislation and regulations are sufficient to guarantee the use of supply chain analytics systems.
- Financial incentives to promote the adoption of supply chain analytics systems are provided.

Supply Chain Analytics Adoption

- Our organization is currently evaluating the usage of supply chain analytics systems.
- Our organization has evaluated and planned the adoption of supply chain analytics systems.
- Our organization has already adopted supply chain analytics systems.

Supply Chain Integration

- There is a collaboration between the production department and suppliers.
- There is a collaboration among shop-floor workers.
- There is a collaboration between the production department and other firms' departments.
- Customers have an active role in new product development.
- Customers have an active role in the production process.

Sustainable Supply Chain Flexibility

- Ability to minimize the cost of green products through process flexibility.
- Ability to reduce transportation time of green products through delivery flexibility.
- Ability to supply green products to customers by resorting to product flexibility.
- Ability to reconfigure the supply chain using flexible supply chain systems.
- Ability to introduce new alternative recycled resources through sourcing flexibility.
- Ability to reduce the waste generated from the supply chain through volume flexibility.
- Ability to increase the speed of acquiring environmental information and response to market flexibility.

Environmental Dynamism

- The rate at which your customer's product/service needs change.
- The rate at which your supplier's skills/capabilities change.
- The rate at which your competitors' products/services change.
- The rate at which your firm's products/services change.

Circular Economy

- Reduction in inputs used (including energy or materials).
- Adoption of more sustainable inputs (e.g., recycled or recyclable materials).
- Move toward greener suppliers.
- Use of waste from other sectors/firms as inputs.
- Reduction in process-related environmental impacts (e.g., on air or water).
- Reduction in production waste.
- Use of the firm's waste in the production process.

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