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Data-Driven Transformation: The Role of Ambidexterity and Analytics Capability in Building Dynamic and Sustainable Supply Chains

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Abstract: Data-driven supply chain analytics skills are seen as the next frontier of the supply chain transformation. The potential of data analytics-enabled dynamic capability for improving organizational performance and agility has been investigated in past research. However, there has not been sufficient research on the potential benefits of the data analytics capability and supply chain ambidexterity paradox to develop a sustainable and agile supply chain that can integrate and reorganize all of its resources in order to respond to rapidly changing business circumstances. This study aimed to empirically validate how an organization's SC ambidexterity affects its sustainability and dynamic capability, and the mediating role of supply chain analytics capability (SCAC) in their relationship. The research's theoretical framework is founded on dynamic capability theory. A pretested questionnaire was used to collect responses from 427 supply chain specialists who worked in diverse product-based industries across Pakistan, Bangladesh, and India. Using partial least squares structural equation modeling (PLS-SEM), a total of six hypotheses were evaluated, and the results show that supply chain ambidexterity has a positive effect on dynamic capability and sustainability, and SCAC plays a complementary, partially mediating role in their interaction. The findings of the research reveal the expected results of investing in the analytics capability of the supply chain and provide firms with some recommendations for improving their dynamic capabilities. This study will facilitate in creating an agile and sustainable supply chain, enabling it to adapt to both short- and long-term changes in the market while simultaneously considering the social, economic, and environmental vitality.

Keywords: supply chain analytics capability; sustainability; ambidexterity; dynamic capability

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1. Introduction

The constant struggle to strike a balance between rapid economic growth and excessive resource consumption encourages firms to engage in highly profitable, environmentally sustainable business activities [1]. Businesses are under pressure to identify such eco-efficient operations that add economic value, as the public's awareness of environmentally friendly corporate practices is continuously increasing [2]. Various scholars have emphasized the significance of addressing the sustainability of supply chain (SC) operations because of the impact of various SC activities on climatic degradation, changes in average weather conditions, and the exhaustion of natural resources [3–5]. Sustainable SC is "the use of collaborative and innovative strategies to integrate economic, environmental, and social aspects for managing the flow of commodities and information within or outside the firm to generate sustainable value" [6]. Agile and sustainable SCs are structurally built in an ambidextrous organization to increase the competitiveness as well as the capacity of any firm to reciprocate promptly in a highly progressive and uncertain market [7]. Ambidexterity refers to the ability or skill to use both hands with equal proficiency. In a broader sense, it can also refer to the ability to perform tasks or exhibit behaviors that require different or opposing skills, qualities, or approaches. Ambidextrous organizations are those that are increasingly using two tactics to stay competitive: exploration (to aspire to new opportunities) and exploitation (to effectively use the existing resources) [8]. Ambidexterity also incorporates the concept of supply chain agility (SCAG), as SCAG defines how any organization responds quickly, according to the fluctuating demand and dynamic market conditions [7]. Developing ambidexterity will enable firms to be both sustainable and agile simultaneously [9].

To remain ambidextrous and deal with the volatile and dynamic situation of the market as well as fulfil social, environmental, and economic vitality, firms are investing heavily in increasing the big data analytics (BDA) capabilities in their SC processes, which will ultimately improve performance and help them to maintain their competitive edge [10]. Big data is a term that describes rapidly growing datasets, and BDA directs the methodology to extract valuable information from these data [11]. BDA has gained prevailing acknowledgment as a cutting-edge innovative technological advancement in business and has drawn burgeoning research interest from the academic community [12,13]. BDA or SC analytics capability (SCAC) for firms can be helpful in discovering the facts, predicting the future outcomes, and strengthening the agility and sustainability of their SC processes [14]. SCAC is a set of abilities that includes the infrastructure adaptability, management aptitude, personnel competence, and data-driven organizational culture of any firm [15]. The effective application of SCAC is based on the assumption that by analyzing massive amounts of unstructured data from different stages of SC operations, meaningful conclusions may be drawn that can help businesses modify their business model [16].

Successful organizations require agile and adaptable SCs that can adapt to longstanding market fluctuations by reorganizing the SC and responding swiftly to short-range shifts in demand [9]. The SC agility (SCAG) is the "aptitude of a firm to counter market uncertainty such as a shift in the consumer' demand regarding variety, quality, or quantity of products, or supply-side failures such as interruptions or shortages" [17]. SC adaptability (SCAD) is "the organization's capacity to implement design changes that are much more drastic and long-lasting than those implemented in accordance with the concept of SCAG" [18]. SCAD and SCAG have been positioned as dynamic capability (DC) since they were developed in response to changes in consumer requirements [9,18,19]. "DC is the ability of any firm to effectively make use of its resources to increase its performance in the rapidly changing market conditions" [20]. DCs can be useful for businesses in identifying threats and opportunities in the marketplace and adapting their structures and resources according to the varying situations [8,21–23]. SCAG is regarded as a key dynamic skill because it enables businesses to recognize market opportunities and risks and to respond quickly with their SCs, while SCAD is a transporting capability because the structure of SC varies with time in response to the marketplace [20]. SCAG and SCAD are important constituents in developing DCs in a firm, but without the sensing capability of the firms to recognize market opportunities, a company's SC would struggle to seize those opportunities and adjust its operations [24]. Market sensing refers to a company's practices to actively learn about its clients, competitors, suppliers, and other stakeholders in the industry in order to understand the market conditions.

Recent research has investigated the effect of SCAC and SC ambidexterity on its resilience, performance, and sustainability. The authors in [25] examined how BDA affected SCAD, operational performance, and cost effectiveness, while the authors in [26] assessed how BDA affected the performance of SC. In [27], the authors explored the relation of BDA with environmental sustainability, while the study in [17] focused on validating the SCAG's role as a mediator between SCAC and performance. The objective of [28] was to observe the effects of BDA on SC sustainability. Similarly, the majority of the existing literature confirms that ambidexterity has a certain influence on organizational performance [29–31].

However, the relation between SCAC, SC ambidexterity, DC and SC sustainability has not been thoroughly investigated yet. Therefore, the following research question was addressed in this research:

RQ. How will SC ambidexterity and SCAC affect the dynamics capability and sustainability of the SC?

The intention of this research was to empirically validate how the SC ambidexterity of any organization impacts its sustainability and DC, which enable it to react to rapid variations in demand and long-standing fluctuations in the market. Additionally, this study will investigate how SCAC mediates a path that connects ambidexterity to DC and sustainability. The research also adds a number of new insights to the existing knowledge. First, it demonstrates how a company's performance in terms of sustainability and agility may be affected by its ability to process data and information, while highlighting the importance of SC ambidexterity in this relationship. Second, it emphasizes the importance of developing SC ambidexterity, or to adapt to changes by using both strategies (i.e., already-existing resources and discovering new ones) [32]. Third, the study also tested a mediation model and empirically validated it to provide a deeper sense of the intricate interrelations between the elements that allow businesses to profit from SC data. Fourth, the findings also help in identifying the essential procedures that businesses might employ to expand their SC sustainability and DC.

The rest of this paper is organized as follows. The information base on SCAC and SC ambidexterity is examined in the following section along with their possible implications on the sustainability of the SC and DCs. In Section 3, a conceptual framework is proposed to link SCAC and SC ambidexterity with DC and SC sustainability. The sampling and data collection procedure is discussed in the Section 4. Section 5 presents the data analysis and model validation. Section 6 discusses the research findings and their implications. The conclusions of our research, its limitations, and prospective areas for further study are covered in Section 7.

2. Literature Review

2.1. Dynamic Capabilities View (DCV)

In [33], the authors developed and suggested the resource base view (RBV) as a strategic technique to comprehend how to establish and maintain a competitive edge. According to the RBV, the distinctions between rivalling firms result from each firm's distinct ability to find and develop a collection of productive, unique, and non-replaceable resources (such as assets, personnel capabilities, operational structure, and information) to generate business value [33]. Many academics have adopted RBV as the basis for their research because SC attempts to optimize the resources of the overall firm [34]. Despite RBV's widespread use, several scholars have criticized it for providing a stagnant perspective of an organization's processes [35].

While RBV has been shown to be effective in recognizing substantial resources for SCAC, much more investigation is required to comprehend how to use resources (personnel, technology, and managerial capabilities) effectively in an environment that is rapidly changing. The extension of RBV is the dynamic capability view (DCV), which was developed by [36]. The dynamic capability view (DCV) underscores the significance of continuously adapting and evolving organizational resources, routines, and processes in response to market dynamics, technological advancements, and customer requirements. This may involve activities such as restructuring supply chain networks, process redesign, technology acquisition, or forging new partnerships to bolster supply chain ambidexterity and sustainability. DCV recognizes the need for organizations to achieve a delicate equilibrium between exploiting existing resources and capabilities and exploring novel opportunities and challenges, a concept known as ambidexterity. The DCV assists firms in identifying the source of corporate value generation and gaining an advantage in competitive marketplaces in dynamic situations. Dynamic capability components such as SCAG, SCAD, and SC visibility can assist businesses and SC stakeholders in combining, developing, and reconfiguring valuable resources to expedite performance and sustainability in an environment that is highly dynamic [19,37]. By incorporating the principles and mechanisms of DCV into their SCM practices, organizations can enhance their agility, responsiveness, and long-term competitiveness amidst evolving market conditions and sustainability concerns. Using prior research, it can be concluded that SCAC and SCAG are valuable DCs that could result in a long-term competitive advantage. SCAC can enhance agility and improve performance using data-driven information.

2.2. Supply Chain Sustainability

In response to the growing expectations of stakeholders, businesses worldwide are increasingly recognizing the significance of addressing the three dimensions of sustainability: profit (economic values), people (social values), and planet (ecological values), often referred to as the triple bottom line (3BL). Measuring the effect of sustainability practices from a 3BL viewpoint on firm performance is essential because it enables the company to determine whether its sustainable policies are having the desired effect [38]. The performance of a company is assessed based on its revenue, productivity, competitiveness, and operating cost ratios [39]. While measuring the corporate performance, the majority of previous studies did not consider the effects of social and environmental practices because the foremost purpose of any business is to make profits or gain a market share [10]. Developing nations plan to pursue economic progress based on decisions made in the short-term. Environmental degradation is causing the temperature to rise, and its effects include the production of solid waste, the contamination of water and the atmosphere, and a decline in green space. However, firms are forced by societies, regulatory bodies, and governments to adopt environmentally friendly activities that include recycling, reuse, reduce, a reduction in energy consumption as well as in the carbon footprint and sustainable consumption of resources [40]. In addition to financial and environmental issues, the society in which the corporation operates is of primary concern [41] as several social issues including gender inequality, malnutrition, child labor, and food scarcity are present in developing countries.

In this research, different constituents were used to measure the economic sustainability of the SC such as profit, market share, energy consumption efficiency, total quality management practices, and operational cost. Similarly, wastewater reduction, air pollution reduction, solid waste reduction, energy consumption performance, and compliance with environmental standards were used to assess the environmental sustainability. Social sustainability indicators are comprised of trustworthiness, the health and safety of employees, gender discrimination, education and training of employees, and policies to control forced and child labor [42].

2.3. Supply Chain Analytics Capability (SCAC)

Big data analytics (BDA) refers to an approach for extracting important information from large amounts of data [11,43]. Big data predictive analytics (BDPA) is a method that employs various algorithm approaches to forecast future events using historical data. The value of BDA has risen tremendously in recent years, and organizations strategically use BDA to gain insights into their SC processes [12]. BDA can be useful to gather information, forecast future events, and lower input costs [14]. In the field of SC, the terms SC analytics (SCA) and BDA are interchangeable. At each point of the SC, enormous amounts of data are produced, and these data and information are shared across all SC participants [44]. For effective decision-making, businesses must create these SCA skills to gather, analyze, evaluate, visualize, and exchange such huge amounts of data [45]. There is empirical evidence from past literature that SCA can increase the productivity and effectiveness [46,47].

Different characteristics that are critical for any organization to establish its SCAC are highlighted in the literature. The first is having an adaptable infrastructure to adopt SCAC, which makes it possible to gather, store, process, and evaluate a lot of information [48]. The second significant aspect in choosing the right SCA infrastructure to use and figure out what kind of data to extract from the databases is the managerial capability [49]. Managers need to be proficient in data analytics to make better data-driven decisions. The third major element is that the staff should have SCA knowledge [10]. Employees should be capable of selecting the relevant data for analysis and derive meaningful conclusions [15]. The information gained by SCA capabilities alters the organizational network connectivity, operational procedures, and strategic approach, which strengthens the organization's capability to create value.

2.4. Supply Chain Ambidexterity

It takes both transformative and incremental change to build sustainable organizations [50]. An ambidextrous firm is able to take advantage to exploit its current resources while also exploring new alternatives [8]. SC exploitation refers to the strategies employed to assist companies in enhancing their current SC capabilities by exploiting current technologies to lower costs and improve reliability, whereas SC exploration involves methods that help people learn different SC skills through experimentation, the adoption of cutting-edge concepts, and innovative research [51]. SC exploitation and exploration enable businesses to quickly address SC problems and modify their SC in response to rapidly changing market situations [9]. Organizations that can efficiently use their current resources and are adaptable enough to handle newly encountered issues are in a superior position to recognize the ongoing threats and risks [32]. According to the literature, ambidexterity comes before agility and is associated with a company's improved capacity to react to market fluctuations [52].

2.5. Dynamic Capability (DC)

DC is the capability of any given organization to integrate and realign all its resources to address the quickly fluctuating business environments [53]. DC has three constituents, the first of which is sensing, defined as the capacity of any firm to identify, assess, and generate opportunities that can satisfy client requirements. The second is seizing or agility: the ability of the company to exploit resources to meet customer expectations or to develop the tools and processes to respond to dynamic changes, and the third is adaptability or reconfiguration, which is to integrate all available resources, assets, and skills to respond the varying market requirements [54]. Sensing and SC visibility are compatible, which permits the accurate tracking of upstream and downstream inventories, production and procurement, and supply–demand dynamics [20]. Successful scanning in the SC encourages businesses to improve their decision-making, planning, and responsiveness [55].

The next stage is the seizing process, which calls for the capacity to be able to take prompt action to create new opportunities [36]. This is also called agility, in that SC issues need to be resolved quickly to adapt to the dynamic business atmosphere [23]. Achieving SC agility enables businesses to effectively integrate with suppliers, efficiently adapt to customer preferences, and offset market fluctuations [24]. The process of dynamic capability-building, which relies on sensing to identify opportunities, is completed by reconfiguration [56]. Flexibility is the capacity to react and adjust to variations while retaining high performance [20]. SC flexibility enables organizations to reduce stock and the resources needed to react to market changes. In light of this, SC flexibility has a favorable impact on operational outcomes such as delivery schedule and overall organizational success such as economic growth [57].

2.6. Research Gap

This brief overview indicates that more research is needed to determine how SCAC and SC ambidexterity together affect SC sustainability and SC dynamics capabilities. This study differs from earlier studies as this study simultaneously analyzed and experimentally validated the impacts of ambidexterity on SC sustainability and DC. It also examined the mediating effects of the SCAC of the firm on sustainability and DC. Exploitation and exploration are two opposing aspects of ambidexterity in a firm, while DC and sustainability are two distinct concepts that coexist in ambidextrous firms. Moreover, different constituents to measure DC and sustainability were extracted from the detailed literature review. For example, three aspects of sustainability (3BL) were measured through a detailed set of questions. Similarly, three dimensions of DC were used including visibility, agility, and adaptability. Moreover, a mediating model was used to assess the effect of SCAC. The research papers that have been published in credible publications on SC sustainability, SC ambidexterity, SCAC, and DC are summarized in Table 1.

Table 1. Summary of publications on SCAC, SC ambidexterity, SC sustainability, and DC.

Sr.	Publication	Region	Type of Industry/ Sample Size	Factors Discussed.							Solution Methodology
				SCAC	AG	SCF	Amb.	Eco.	Envr.	Soc.	
1.	[4]	India	Manufacturing/ 297 responses	✓	✓				✓	✓	SEM and ANN
2.	[58]	China	Manufacturing/ 307 responses	✓				✓			SEM
3.	[59]	India	Manufacturing/ 106 responses	✓					✓	✓	SEM
4.	[25]	NA	SC professionals/ 281 responses	✓	✓		✓	✓			SEM
5.	[29]	NA	SC managers/ 239 responses	✓			✓				SEM
6.	[9]	Pakistan	Manufacturing/ 277 responses	✓	✓	✓	✓				SEM
7.	[26]	South Africa	Mining/ 520 responses	✓			✓		✓		SEM
8.	[60]	India	Data analytics professionals/ 209 responses	✓				✓			SEM
9.	[61]	China	Manufacturing/ 206 responses	✓					✓	✓	Hierarchical multiple regression
10.	[27]	NA	Automobile and Airline Industry/ 145 responses	✓					✓		Qualitative and quantitative
11.	[17]	USA	Supply chain managers/ 281 responses	✓	✓						SEM
12.	[28]	Iran	Pharmaceutical/ 188 responses	✓				✓			SEM
13.	[5]	India	SC managers/ 173 responses	✓					✓	✓	SEM
14.	[62]	India	Manufacturing/ 213 responses	✓		✓					SEM
15.	[63]	Europe	Supply chain managers/ 259 responses	✓	✓		✓				SEM
16.	[40]	India	Supply chain managers/ 316 responses	✓				✓	✓		SEM and ANN
17.	[2]	Golf-Cooperation Countries	Professionals/ 215 responses	✓					✓		SEM

Table 1. *Cont.*

Sr.	Publication	Region	Type of Industry/ Sample Size	Factors Discussed. SCAC	AG	SCF	Amb.	Eco.	Envr.	Soc.	Solution Methodology
18.	[64]	India	SC managers/ 173 responses	✓	✓	✓					SEM
19.	[10]	NA	Automobiles/ 205 responses	✓				✓	✓	✓	SEM
20.	[57]	NA	IT professionals/ 215 responses	✓	✓						SEM
21.	[32]	NA	NA	✓	✓		✓				Conceptual framework
22.	[31]	China	Manufacturing/ 206 responses	✓			✓				Least square regression
23.	[65]	France	SC professionals/ 404 responses	✓			✓	✓	✓	✓	SEM
24.	[66]	Iran	IT professionals/ 187 responses	✓			✓				SEM
25.	[67]	Malaysia	Service firms/ 145 responses	✓		✓					SEM
26.	This research	Pakistan, India, and Bangladesh	SC managers/ 427 responses	✓	✓	✓	✓	✓	✓	✓	SEM

SCAC: supply chain analytics capability, AG: agility, SCF: supply chain flexibility, Amb.: ambidexterity, Eco.: economic sustainability, Envr.: environmental sustainability, Soc.: social sustainability, SEM: structural equation modeling, ANN: artificial neural network.

3. Hypotheses Development

3.1. The Relationship between SC Ambidexterity and DC

In the extremely complicated business environment, SC ambidexterity can provide an edge over competitors [25]. Improving an organization's exploitation and exploration capabilities may promote responsiveness and adaptability, two distinctive characteristics of any corporation [68,69]. In order to analyze the conflicts between exploration and exploitation, extensive research has been carried out in the context of the SC literature [70–72]. In these research streams, ambidextrous SC strategy [70], cost efficiency [73], agility [71], adaptability [9], and resilience [21] have all been examined. The authors in [20] argued that SC ambidexterity is a crucial attribute that supports the companies to moderate the effects of SC interruptions and helps in improving the performance of a firm. However, there is still a study vacuum regarding the role that ambidexterity plays in improving the DC of a firm. Therefore, the first hypothesis of this research was developed:

H1: *SC ambidexterity has a significant positive effect on the SC dynamic capability (DC).*

For this hypothesis, SC ambidexterity is the independent variable while DC is the dependent variable. Organizations can create an environment conducive to the emergence of DCs through the pursuit of SC ambidexterity. SC ambidexterity involves striking a balance between exploiting existing resources and exploring new opportunities, enabling organizations to be more adaptive, agile, and responsive to market and industry changes. It serves as an input variable that lays the foundation for the development and deployment of DCs within the organization. Achieving SC ambidexterity establishes an environment that supports and strengthens DCs, resulting in heightened adaptability, innovation, and sustained competitive advantage.

3.2. The Relationship between SC Ambidexterity and SC Sustainability

Businesses must change their current operations to become more adaptable to survive in today's complicated and dynamic situation. It is argued that SC ambidexterity enables businesses to effectively manage existing business requirements while also being fundamentally adaptable to sudden variations [74,75]. Prior research has investigated the effects of ambidexterity on many metrics including corporate performance, SC competence, and supplier product development [76–78]. It is true that organizational theory has given SC ambidexterity a lot of attention, and it is commonly accepted that ambidexterity is required for maintaining the organizations' competitive advantages while taking both the current and future performance into account [79–81]. According to [75], there is a link between sustainability and ambidexterity, since improving production lines, while also adapting them to balance the TBL aspects, is necessary for organizational sustainability. Ambidexterity helps businesses to manage their business environment successfully and creates a system that is flexible to respond and adapt to change [75,82]. In light of this discussion, the following hypothesis was added in this research, related to SC ambidexterity and SC sustainability.

H2: *SC ambidexterity has a significant positive effect on SC sustainability.*

In this hypothesis, SC ambidexterity is the independent variable and SC sustainability is the dependent variable. By achieving supply chain ambidexterity, organizations effectively balance resource optimization and the exploration of new opportunities. This enables them to enhance operational efficiency, minimize waste, and improve resource utilization. Supply chain ambidexterity fosters collaborations, sustainable relationships, and responsible labor practices. It also supports economic sustainability through innovation, adaptability, and responsiveness to market trends. Overall, supply chain ambidexterity drives optimization, collaboration, innovation, and sustainability.

3.3. The Relationship between SCAC and SC Dynamic Capability (DC)

SC visibility has been described in earlier research as an organizational ability that might reduce the consequences of a disturbance in the SC [19,83]. In order to make the SC more transparent, information-sharing and visibility are important characteristics. Information sharing is the relevancy of the delivered information, while visibility is the flow of information about the product's demand and its available inventory at a particular time [37]. Businesses should concentrate on building their SC connections to increase their visibility in order to provide accurate and pertinent information [37]. The use of BDAC can further increase SC visibility and performance by minimizing the detrimental impact of demand fluctuation in the SC, enabling firms to be more agile [84] and adaptable [19,85]. Using BDAC or SCAC may assist managers to detect quick changes in the environment and build business continuity strategies that may enable them to react to these changes promptly [86]. Visibility, agility, and adaptability are all constituents of dynamic capability. Therefore, a further two hypotheses in this research are:

H3: *SCAC has a significant positive effect on the SC dynamic capability.*

H5: *SCAC mediates the relation between the SC dynamic capability and ambidexterity.*

For Hypothesis 3, SCAC is the independent variable while the SC dynamic capability is the dependent variable, while for Hypothesis 5, ambidexterity is the independent variable and the SC dynamic capability is the dependent variable while SCAC mediates the relation between them. The relationship between the SCAC and SC dynamic capability is closely intertwined and mutually beneficial. SCAC acts as a crucial building block for the development and implementation of DC. By harnessing analytics tools and techniques, organizations can extract valuable insights from their SC operations, pinpoint areas that require improvement, and make informed decisions based on data-driven analysis. SCAC enables data-driven decision-making for SC activities. It helps identify exploration and exploitation opportunities, align strategies with ambidexterity principles, optimize operations, and allocate resources. SCAC leverages advanced analytics techniques to gain deep insights into SC dynamics, performance, and customer behavior. These insights inform the development of SC's dynamic capability, facilitating informed decisions and effective responses to market changes.

3.4. The Relationship between SCAC and SC Sustainability

Businesses compete intensely to increase their market share in today's industry. To be capable of providing shareholder returns, businesses must remain profitable, but the aspect of sustainability goes beyond only financial gains. Sustainable development is defined as an approach that aims to satisfy the existing needs without jeopardizing the future ability to satisfy these needs. Environmental and ethical concerns are continually influencing the consumers' purchase decisions. Programs such as "reduce, reuse, and recycle" can help in achieving environmental sustainability goals. In [87], the authors argued that using BDA significantly bolstered the financial, ethical, and social advantages in Europe. In actuality, the SC performance in terms of 3BL is significantly impacted by predictive analytics skills [10]. Additionally, Refs. [12,13] empirically investigated that BDPA had a substantial impact on the financial standings.

The results of a company's strategic actions that control its effects on the environment are called environmental performance. These results include how well the organization performs in a number of areas such as energy conservation, solid waste, air pollution, resource waste, and other negative environmental repercussions [88]. Numerous empirical studies have concentrated on various tactics to enhance the performance of the environment [88–91], and studies that provide empirical evidence of the effect of BDA on environment sustainability can be found in [5,27,92,93]. Several other research papers have revealed that the BDA capabilities, when used with the proper monitoring and analytic methods, could improve resource usage and enhance energy efficiency.

After the environment, the third area of concern is the society in which businesses operate [61]. Although many nations' standards of living are rising, some countries still struggle to meet their necessities of life. Developing economies face a number of obstacles in the areas of equity, gender parity, child labor, hunger, and healthy working conditions [10]. Economic performance can be measured through different indicators in financial statements and stock markets. Moreover, the Global Reporting Initiative or ISO 14001 are used to measure environmental performance, but due to difficulties in obtaining tangible results and the complexity of the involved human issues, the social aspect of sustainability has not received enough attention [5]. This is driving corporations to realize the value of social responsibility and how it affects their performance [94]. Customers and other stakeholders anticipate businesses to be accountable for profitability, a healthy environment, and moral conduct [95,96]. The authors in [97] argued that the BDAC has the capacity to improve social performance. Therefore, from the sustainability perspective, the last two hypotheses in this research are:

H4: *SCAC has a significant positive effect on SC sustainability.*

H6: *SCAC mediates the relation between ambidexterity and SC sustainability.*

For Hypothesis 4, SCAC is the independent variable while SC sustainability is the dependent variable. For Hypothesis 6, SCAC mediates the relationship between ambidexterity (independent) and SC sustainability (dependent). SCAC plays a vital role in enhancing supply chain sustainability. By leveraging data-driven decisions, monitoring performance, and promoting continuous improvement, organizations can achieve their sustainability goals. SCAC acts as a mediator between ambidexterity and SC sustainability by providing insights, monitoring performance, and supporting data-driven decision-making. It aligns ambidextrous actions with sustainability goals, improving the overall SC sustainability.

3.5. Research Model

This study's theoretical framework was based on DCV. DCV is popular among scholars who need to assess how integrating the firm assets and personnel capabilities might increase the firm's competitiveness in a highly unpredictable environment. The need for SCAC is further increased by variable and complex work situations, where efficient decision-making is exceedingly challenging due to high levels of uncertainty. The theoretical framework is made up of several dimensions, which are presented in Figure 1. A link can be drawn from SC ambidexterity to SC sustainability and SC dynamic capability (Hypotheses 1 and 2). Moreover, the SC analytics capability was added to find its mediating effect on SC dynamic capability and SC sustainability (Hypotheses 3, 4, 5, and 6).

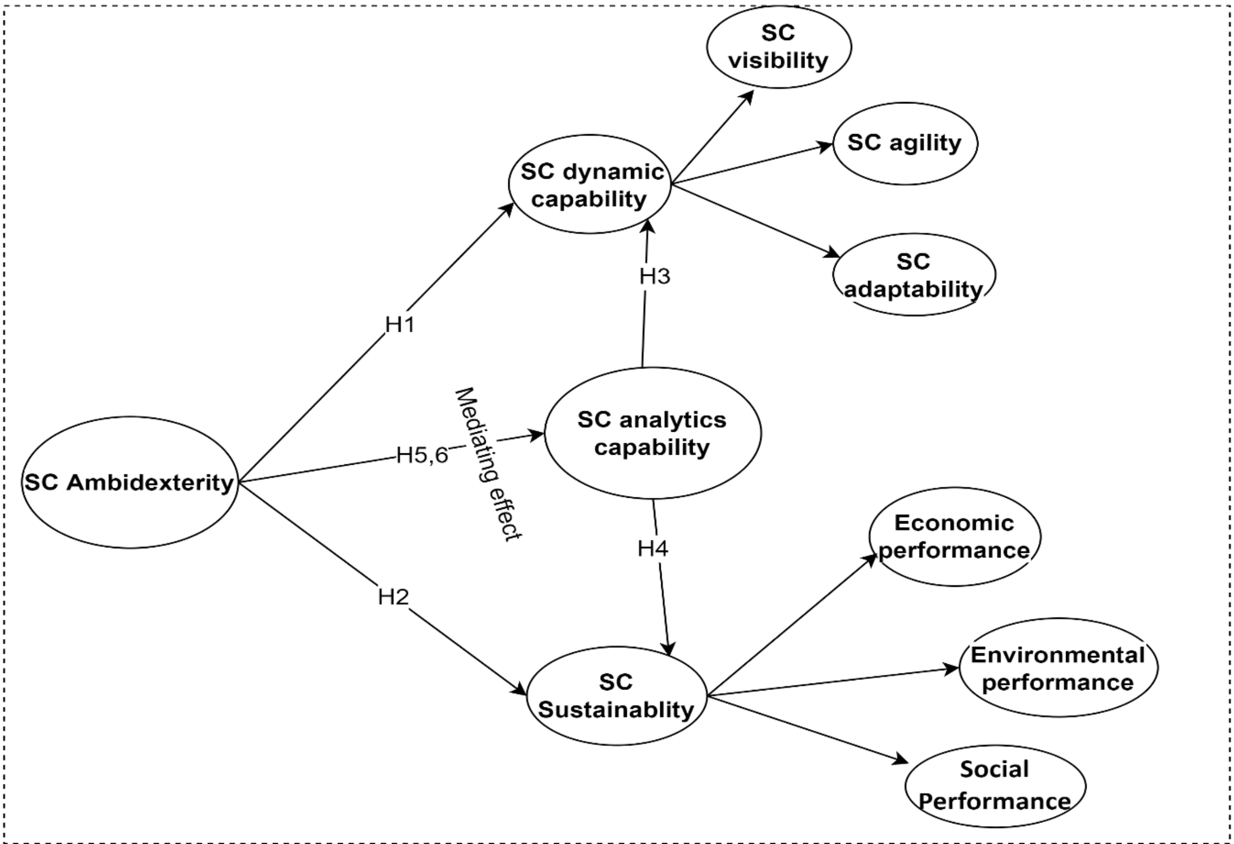

Figure 1. Conceptual framework.

4. Research Design

The data collection process began by creating a pretested questionnaire, which was developed through an extensive review of the relevant literature and theoretical frameworks. The questionnaire encompassed items pertaining to SC ambidexterity, SC sustainability, dynamic capability, and SCAC. The survey was designed on Google Forms and a 5-point Likert scale ranging from strongly agree (1) to strongly disagree (5) was employed in all of the responses. To ensure the questionnaire's clarity, validity, and reliability, a pilot test was conducted with a small group of SC professionals. After the pilot testing, feedback from both academics and senior SC managers was solicited to refine the questionnaire. Their valuable input was used to enhance the wording of the questionnaire items, address any ambiguity, and ensure the instrument's relevance and comprehensiveness. The iterative process of feedback and refinement resulted in an improved questionnaire for the subsequent data collection phase. A final sample of 2295 SC managers from three South Asian countries—Pakistan, India and Bangladesh—was chosen to participate in the study. To ensure diverse representation from the three countries, various industries, organizational sizes, and experience of the SC professionals, a stratified random sampling approach was employed in this study. The target population consisted of SC managers and executives from different sectors. Stratification was based on country, industry type, company size, and the experience of the SC managers. Within each stratum, a random sample of participants was selected, ensuring that the sample represented each industry.

4.1. Construct Operationalization

The variables and constructs for the survey were chosen from the literature. All of the constructs of the conceptual framework were taken as reflective. The four constructs that make up the higher order reflective construct for SCAC were the SC managerial capability, organizational capability, personnel resource capability, and data-directed culture of the organization. SC ambidexterity was assessed using exploitative and explorative capabilities through an eight item scale. SC sustainability had three dimensions. Similarly, dynamic capability was measured through SC visibility, SC agility, and SC adaptability. Table A1 in Appendix A provides specific operationalization information for each component along with the related literature.

4.2. Data Collection

Employees at the manager level who were experts at tasks associated with the procurement, production, inventory, warehousing, purchasing, shipping, and logistics made up the target respondents. The information from the SC specialists employed in various industries was gathered by using two platforms. One of these was a B2B database that provided information on various SC experts working in various firms in Pakistan, Bangladesh, and India. The second source was LinkedIn, which was used to search for information of supply chain managers employed in different companies in the above-mentioned countries. The researchers also contacted the respondents through telephone and personally visited companies located in Pakistan to persuade them to complete the survey. In total, 495 completely filled-in surveys were received between May and September 2022. The survey's response rate, which was 22%, was consistent with that of earlier surveys in previous studies. The survey's findings were carefully examined. The responses were reviewed using the key informant approach. All respondents whose job descriptions were not associated with SC operations were eliminated and the responses with missing details were removed. The total dataset consisted of 427 valid responses. Table A2 in Appendix B contains descriptive statistics related to the data.

Since larger businesses often have better access to more resources, the majority of the data were gathered from large-sized businesses. Similarly, data were gathered from several sectors, and Table 2 shows all of the demographic information for the valid responses that was used for the data analysis. A non-response bias test was conducted to investigate whether there were any variations among the late and early respondents using a paired *t*-test. In order to perform this, 100 early and 100 late responses were examined, and it was found that there were no significant differences (Appendix C, Table A3). As a result, the analysis did not raise any concerns regarding a non-response bias.

Table 2. Characteristics of the respondents.

Characteristics of the Respondents (Sample = 427)	Number	Percentage
Country's Name		
Pakistan	209	48.9%
India	120	28.1%
Bangladesh	98	22.1%
Firm Size (number of employees)		
Small (10–49)	26	6.0%
Medium (50–249)	62	14.5%
Large (>250)	339	79.3%

Table 2. *Cont.*

Characteristics of the Respondents (Sample = 427)	Number	Percentage
Experience of SC professional		
1–3 years	68	15.9%
4–7 years	108	25.2%
7–10 years	83	19.4%
More than 10 years	168	39.3%
Sector		
Heavy manufacturing	20	4.68%
Fast moving consumer goods (FMCG)	122	28.5%
Automobiles	46	10.7%
Pharmaceuticals	89	20.8%
Textiles and apparel	128	29.9%
Packaging	22	5.15%

4.3. Common Method Bias (CMB)

For survey-based research data, there is a chance for CMB, which causes the indicators to exhibit some similar variation [98,99]. Scholars have used procedural remedies to reduce the effect of CMB on the proposed model. Ex ante and post ante tests were also conducted for CMB by following [99]. Data were carefully collected from people with relevant knowledge of the topic for ex ante analysis. The likelihood of CMB was decreased because SC respondents had the required level of subject understanding. Additionally, to prevent misinterpretation, the specific questions were clearly written, and the respondents' anonymity was guaranteed. A post hoc analysis was performed to determine whether CMB existed, in accordance with the one factor test proposed by [100]. The exploratory factor analysis revealed several components, with one factor best explaining 25.98% of the variation. This result showed that there was no issue of CMB in this study.

One of the most important tests for CMB has been the use of marker variables. This is in response to claims that Harman's method does not offer a valid test for CMB [101]. The research model was compared against a model that incorporated a marker variable that has no theoretical affiliation to any of the variables of the model [102]. The significance of the relationships did not alter when the market variable was included in the model. Based on these statistics, it can be claimed there are no significance impacts of common method bias (CMB) on this model (Appendix D, Table A4).

5. Data Analyses and Results

Smart PLS 4.0 was used to apply structural equation modeling for this study [103]. SmartPLS 4.0 is a software tool specifically designed to support the partial least squares structural equation modeling (PLS-SEM) approach. PLS-SEM is particularly advantageous for analyzing complex models without assuming specific data distributions such as normality assumptions [104]. It allows researchers to effectively estimate intricate models with multiple constructs and indicators [105]. A key feature of SmartPLS is its provision of bootstrapping techniques and Monte Carlo simulations. These features are valuable in assessing the significance of path coefficients, conducting hypothesis testing, and evaluating the stability and robustness of the model. SmartPLS excels in assessing data heterogeneity in various forms including observed and unobserved heterogeneity. It supports moderation analysis, nonlinear effects, multi-group analysis for observed heterogeneity, while for unobserved heterogeneity, it enables segmentation using FIMIX-PLS [106]. This study also employed a complex model with a total of twelve lower-order and four higher-order constructs including a construct for the mediation effect. PLS-statistical SEM's features allow for reasonably accurate model predictions for both normal and irregularly non-normally distributed data [107]. The SEMinR package of R, a strong, user-friendly resource for specifying and evaluating difficult structural equation models (SEM), was also used to cross-validate all of the results [108]. A procedure was employed to construct and evaluate SEM using specific syntax. The process of specifying and estimating SEM involved four key steps: (1) preparing and refining the data; (2) defining the measurement models; (3) outlining the structural model; (4) estimating, bootstrapping, and summarizing the model. In order to verify the obtained outcomes, the results generated by SEMinR were cross-checked against those obtained from SmartPLS. Visit the given link to access the SEMinR package codes for R that were developed for this research (https://github.com/Adeelmunir158/SEMinR_Sustainability, (accessed on 1 June 2023)). The model was assessed using the following three steps: (1) measurement model; (2) structural model; (3) the model's robustness.

5.1. Measurement Model

5.1.1. Lower-Order Constructs

Every item of the lower-order constructs contained factor loadings that were greater than the 0.5 minimum allowed value. A factor loading measures the degree of association between an item (indicator) and its underlying construct in factor analysis. Typically, a factor loading of 0.5 or greater is regarded as statistically significant, signifying a relatively robust relationship [109]. The loadings with values <0.70 are considered weak, but they are all eliminated only if their removal improves the average variance extracted (AVE) or composite reliability (CR) [110]. The loading values between 0.5 and 0.7 indicate that the identified items did not make a significant contribution to the measurement of their corresponding constructs. In SEM analysis, it is a common practice to remove items with lower loading values to enhance the overall reliability and validity of the measurement model.

During the assessment of items and their loading values, the primary objective of the researcher was to retain the items that exhibited strong associations with the construct and enhance the overall reliability and validity of the measurement model. The aim of the researcher was to strike a balance between capturing the fundamental nature of the construct while maintaining a measurement model that is both reliable and valid. Therefore, one item was removed (Visibility1) from the construct "Visibility" because its outer loading value was lower than 0.5. Similarly, one item (Agility4) was removed from "Agility" because its removal improved the AVE from 0.472 to 0.515. Another item (Adapt5) was deleted, due to which the AVE of "Adaptability" was increased from 0.463 to 0.534, as shown in Table 3. No remaining items were eliminated because the factor loading of all variables was significant, as assessed by bootstrapping.

Table 3. Reliability and validity analysis of the lower-order constructs.

Constructs	Item	Loadings	Cronbach's Alpha	CR (rho_a)	CR (rho_c)	(AVE)
Technical capability	TC1	0.781	0.775	0.782	0.870	0.690
	TC2	0.875				
	TC3	0.834				
Management capability	MC1	0.800	0.747	0.748	0.855	0.664
	MC2	0.833				
	MC3	0.811				
Human resource capability	HC1	0.858	0.712	0.719	0.839	0.636
	HC2	0.811				
	HC3	0.717				
Data-driven culture	DD1	0.911	0.778	0.795	0.871	0.694
	DD2	0.768				
	DD3	0.814				

Table 3. *Cont.*

Constructs	Item	Loadings	Cronbach's Alpha	CR (rho_a)	CR (rho_c)	(AVE)
Exploitative capability	Exploit1	0.755	0.774	0.775	0.855	0.596
	Exploit2	0.754				
	Exploit3	0.775				
	Exploit4	0.805				
Explorative capability	Explore1	0.784	0.781	0.803	0.860	0.607
	Explore2	0.650				
	Explore3	0.868				
	Explore4	0.800				
Visibility	Visibility1	Deleted	0.727	0.722	0.843	0.643
	Visibility2	0.817				
	Visibility3	0.856				
	Visibility4	0.727				
Agility	Agility1	0.687	0.766	0.770	0.841	0.515
	Agility2	0.755				
	Agility3	0.738				
	Agility4	Deleted				
	Agility5	0.676				
	Agility6	0.730				
Adaptability	Adapt1	0.717	0.712	0.734	0.820	0.534
	Adapt2	0.682				
	Adapt3	0.709				
	Adapt4	0.808				
	Adapt5	Deleted				
Economic	Econom1	0.707	0.799	0.885	0.853	0.538
	Econom2	0.737				
	Econom3	0.767				
	Econom4	0.65				
	Econom5	0.799				
Environmental	Environ1	0.777	0.832	0.859	0.884	0.610
	Environ2	0.869				
	Environ3	0.87				
	Environ4	0.817				
	Environ5	0.516				
Social	Social1	0.764	0.855	0.858	0.896	0.632
	Social2	0.816				
	Social3	0.788				
	Social4	0.795				
	Social5	0.812				

Reliability was assessed using Cronbach's alpha, and CR; all values were higher than 0.700 [111], as shown in Table 3, indicating good reliability [112]. CR (rho_a) and CR (rho_c) are both measures used in assessing the internal consistency. However, (rho_a) is less robust to measurement error heterogeneity as it assumes equal error variances across all indicators. CR (rho_c) is more robust to measurement error heterogeneity as it allows for variations in error variances across indicators. Additionally, the AVE values for all variables surpassed the required limit of 0.50, showing that all constructs had acceptable convergent validity. To evaluate the discriminant validity, the first set of criteria was proposed by [113], which required that the $\sqrt{AVE}$ for each construct be greater than its correlation with all other constructs. Table 4 shows that it meets the required conditions. The second method was to look at the heterotrait–monotrait (HTMT) ratio for each construct, which also validated the constructs' discriminant validity as all values fell below the cut-off value of 0.90 [114].

Table 4. Fornell–Larcker criterion and HTMT for the lower-order constructs.

	Adapt.	Agile	DD	Eco.	Env.	Exploit.	Explore	HC	MC	Social	TC	Visi.
Adapt	***0.73***	0.79	0.61	0.34	0.33	0.66	0.65	0.62	0.66	0.35	0.65	0.81
Agile	0.59	***0.72***	0.62	0.33	0.27	0.67	0.55	0.59	0.70	0.28	0.58	0.71
DD	0.47	0.50	***0.83***	0.28	0.26	0.58	0.54	0.78	0.84	0.31	0.69	0.63
Eco	0.30	0.29	0.25	***0.73***	0.69	0.44	0.34	0.27	0.37	0.55	0.28	0.36
Env	0.26	0.22	0.22	0.51	***0.78***	0.36	0.22	0.31	0.35	0.74	0.30	0.31
Exploit	0.51	0.53	0.46	0.41	0.29	***0.77***	0.74	0.53	0.69	0.36	0.57	0.63
Explore	0.50	0.43	0.44	0.31	0.19	0.59	***0.78***	0.54	0.64	0.27	0.59	0.56
HC	0.46	0.45	0.59	0.24	0.25	0.40	0.41	***0.80***	0.84	0.31	0.81	0.68
MC	0.49	0.54	0.64	0.31	0.27	0.52	0.50	0.62	***0.82***	0.27	0.85	0.73
Social	0.28	0.24	0.26	0.45	0.63	0.29	0.23	0.25	0.22	***0.80***	0.26	0.24
TC	0.49	0.46	0.54	0.25	0.24	0.44	0.47	0.61	0.65	0.21	***0.83***	0.70
Visi	0.60	0.57	0.49	0.31	0.25	0.49	0.44	0.52	0.55	0.21	0.55	***0.80***

Note: The values shown in the diagonal row (bold and italic) are the square root of AVE. The values below the diagonal row represent the Pearson correlations among the constructs and values above the diagonal row are the HTMT values. Abbreviations: TC, technical capability; MC, management capability; HC, human resource capability; DD, data driven; Exploit., exploitative; Explore, explorative; Visi., visibility; Agile, agility; Adapt., adaptability; Eco., economic; Env., environmental.

5.1.2. Higher-Order Constructs

In this study, SCAC, SC sustainability, SC dynamic capability, and SC ambidexterity were used as higher-order constructs. SCAC consists of four lower-order components: SC management capability, technical or infrastructural capability, human resource capability, and data-driven culture of the company. Similarly, exploitative and exploratory capabilities were used to measure the SC ambidexterity. DC was measured from three lower-order constructs (i.e., SC visibility, agility, and adaptability). Sustainability was measured from 3BL. All values of the factor loadings of higher-order constructs were greater than 0.5 [109]. All indicators of reliability were satisfactory, as the values of the Cronbach's alpha and CR, as mentioned in Table 5, were of acceptable level. The AVE values established convergent validity.

Table 5. Reliability and validity analysis of the higher-order constructs.

Constructs	Item	Loadings	(VIF)	Cronbach's Alpha	CR (rho_a)	CR (rho_c)	(AVE)
(SCAC)	Technical	0.831	1.822	0.861	0.864	0.906	0.706
	Management	0.875	1.728				
	Human resource	0.829	1.924				
	Data driven	0.824	1.409				
SC ambidexterity	Exploitative	0.904	1.865	0.744	0.749	0.886	0.796
	Explorative	0.88	1.54				
SC dynamic capability	Visibility	0.851	1.54	0.809	0.809	0.887	0.723
	Agility	0.844	1.979				
	Adaptability	0.856	2.299				
SC sustainability	Economic	0.828	1.722	0.773	0.785	0.867	0.685
	Environmental	0.84	1.976				
	Social	0.814	1.738				

Discriminant validity was also established as every construct's $\sqrt{AVE}$ exceeded its correlation with all other constructs [113], and the HTMT ratio (see Table 6) was likewise below the 0.90 criterion [114].

Table 6. Fornell–Larcker criterion and HTMT for the higher-order constructs.

	Ambidexterity	Dynamic Capability	SCAC	Sustainability
Ambidexterity	***0.892***	0.821	0.757	0.510
Dynamic capability	0.638	***0.850***	0.834	0.468
SCAC	0.608	0.697	***0.840***	0.435
Sustainability	0.399	0.375	0.358	***0.828***

Note: The values shown in the diagonal row (bold and italic) are the square root of AVE. The values below the diagonal row represent the correlations among the constructs, and values above the diagonal row are the HTMT values.

5.2. Structural Model Analysis

In the initial step, the multicollinearity test was performed using the variance inflation factor (VIF). The multicollinearity test is performed to evaluate whether predictor variables in a regression analysis exhibit strong correlations. The variance inflation factor (VIF) is a popular technique used to detect multicollinearity. It quantifies how much the variance of an estimated regression coefficient is inflated due to multicollinearity. A VIF value of 1 suggests the absence of multicollinearity, while higher values indicate increasing levels of multicollinearity. Typically, VIF values above 3.3 are considered indicative of significant multicollinearity [115]. The specified threshold was not reached by any of the VIF values for the outer model's constructs (see Table 5).

The VIF values of SCAC with ambidexterity and dynamic capability for the inner model were 1 and 1.587, respectively. Moreover, the VIF for both (i.e., ambidexterity with dynamic capability and sustainability) was also 1.587. Finally, the VIF of SCAC with sustainability was also computed as 1.587. The standardized root mean square residual (SRMR) was used to assess the model quality, and a value of 0.063, which was less than the desired value of 0.08, was considered to be a good match [116]. The normed fit index (NFI) is a statistical metric widely employed in SEM to evaluate the suitability of a proposed model in relation to the observed data. In this case, the NFI value of 0.80 suggests that the proposed model fit the data somewhat below the desired threshold of 0.90. A lower fit value means that the model accounts for less variance in the observed data. However, the predictive power of the model was further explored in PLS predict (Section 5.3) and its outcomes were deemed acceptable. Other metrics such as R^2 and Stone–Geisser also provided satisfactory results (Table 9).

Figure 2 presents the detailed analysis of the structural model. It not only shows the values of the factor loadings for each higher-order construct (also shown in Table 5), but also provides the beta coefficient values that represent the relationship between each construct, as given in Tables 7 and 8. Moreover, the value in blue circles shows the coefficient of determination (R^2) of the dependent variables. Through bootstrapping, the findings showed that SC ambidexterity substantially impacted the DC (β = 0.340, t = 7.599). The second hypothesis was also validated, which claims that ambidexterity has a significant positive impact on SC sustainability (β = 0.289, t = 5.175). In addition, the third and fourth hypotheses regarding the significant influence of SCAC on DC (β = 0.490, t = 10.972) and SC sustainability (β = 0.182, t = 3.239) were also validated (Table 7).

Table 7. Direct relationships of the constructs.

Hypothesis	Beta Coefficient	Standard Deviation	T Statistics (Bootstrap)	*p*-Values	Result
H1: Ambidexterity → Dynamic capability	0.340	0.045	7.599	0.000	Supported
H2: Ambidexterity → SC sustainability	0.289	0.056	5.175	0.000	Supported
H3: SCAC → Dynamic capability	0.490	0.045	10.972	0.000	Supported
H4: SCAC → SC sustainability	0.182	0.056	3.239	0.000	Supported

Table 8. Mediation analysis results.

Total Effect		Direct Effect		Indirect Effect				Result
Coefficient	*p*-Value	Coefficient	*p*-Value	Hypothesis	Coefficient	T-Value (Bootstrap)	*p*-Value	
0.638	0.000	0.340	0.000	H5: Ambidexterity → SCAC → Dynamic capability	0.298	8.983	0.000	Supported
0.399	0.000	0.289	0.000	H6: Ambidexterity → SCAC → SC sustainability	0.110	3.062	0.000	Supported

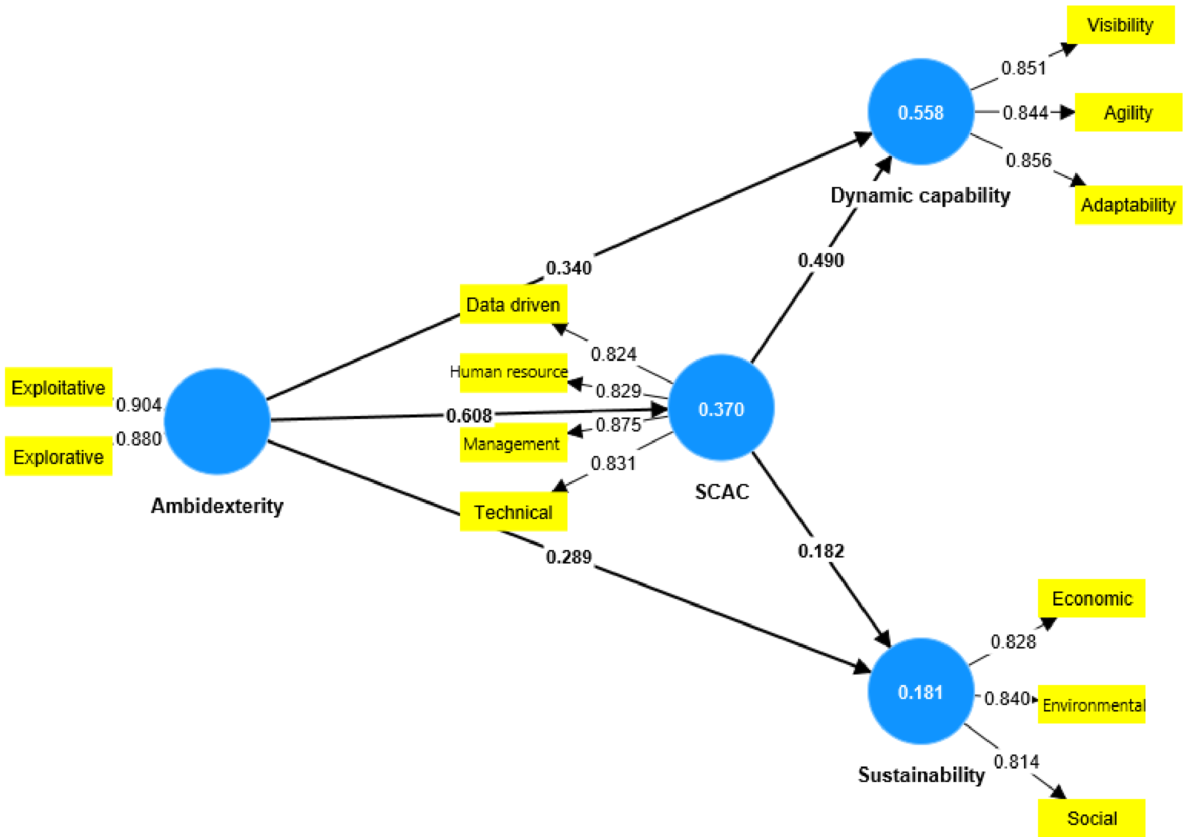

Figure 2. Structural model.

A mediation study using bootstrapping was carried out to assess the mediation role of SCAC between ambidexterity and DC as well as SC sustainability. The results revealed that there was a significant indirect effect of SC ambidexterity on DC (β = 0.298, t = 8.983). The total effect of SC ambidexterity on DC was (β = 0.638, t = 19.812), which was still significant after the addition of a mediator (β = 0.340, t = 7.599). This validates the fifth hypothesis and demonstrates that SC ambidexterity has a complementary, partial mediating role between SCAC and DC.

The final hypothesis was about the mediating role of SCAC between ambidexterity and sustainability. The indirect role of SC ambidexterity on SC sustainability is (β = 0.298, t = 8.983) was significant. The total significant effect was (β = 0.399, t = 9.075), which was still significant after the inclusion of SCAC as a mediator (β = 0.289, t = 5.175). This reveals that SC ambidexterity has a complementary, partial mediating role between SCAC and SC sustainability.

In this research, the R^2 value of dynamic capability, SCAC, and SC sustainability were 0.558, 0.370, and 0.181, respectively, as shown in Table 9. The R^2 values need to be larger than 0.1 [117]. According to the criteria in [118], the R^2 value of DC and SCAC was substantial and for SC sustainability, it was moderate. However, by following [119,120], the R^2 value of DC and SCAC was moderate, and weak for SC sustainability.

Table 9. The R^2, prediction, and effect size.

			f^2 in Relation with		
Construct	**R^2**	**Q^2**	**Ambidexterity**	**Dynamic Capability**	**SC Sustainability**
SCAC	0.370	0.366	0.587	0.343	0.026
Dynamic capability	0.558	0.404	0.165		
SC sustainability	0.181	0.152	0.064		

The difference in R^2 with the removal of an independent variable is called the effect size (f^2). For this study, ambidexterity had a medium effect size on DC (f^2 = 0.165) and a weak effect size on sustainability (f^2 = 0.064), as per the recommendations in [118]. However, SCAC had a large effect size on DC (f^2 = 0.343), but a small effect size on sustainability (f^2 = 0.026).

The Stone–Geisser (Q^2) is used to estimate the predictive relevance. Any given model is predictively relevant when the Q^2 is greater than zero [120]. To calculate the Q^2 value, the blindfolding method was used in SmartPLS. The (Q^2) values for SCAC, dynamic capability, and SC sustainability were 0.366, 0.404, and 0.152, respectively.

5.3. PLSpredict

PLSpredict, a method for out-of-sample prediction, was employed to evaluate the predictive accuracy as indicated by [121]. Several commonly employed evaluation metrics are utilized to assess the accuracy of predictions including the mean squared error (MSE), which computes the average of the squared differences between the predicted values and the actual values; the root mean squared error (RMSE), which is the square root of the MSE and offers a measure of the average magnitude of the prediction errors; the mean absolute error (MAE), which calculates the average absolute difference between the predicted and actual values. It provides a robust measure of prediction accuracy as it is less affected by outliers. The Kolmogorov–Smirnov test was used to evaluate the prediction error distribution, which was found to be nonsymmetric, as seen in Table A5 in Appendix E. Therefore, the mean absolute error (MAE) was used to compute the degree of prediction error. Table A6 in Appendix F contains the values of Q^2 predict for dependent and mediator construct items as well as a comparison of each indicator's PLS-SEM-MAE with a benchmark using a simple linear regression model (LM-MAE). The majority of the indicators of the PLS-SEM analysis could be seen to have lower prediction errors, indicating a medium predictive power.

Necessary Condition Analysis (NCA)

Developed originally by [122], NCA is a method and tool that is used for the identification of necessary conditions in given sets of data. Figure 3 illustrates how NCA creates a ceiling line on top of the provided data [123]. The ceiling line displays the lowest level of the independent variable required to achieve a definite level of the dependent variable. The bottleneck table includes a summary, and the first column is the outcome while the remaining columns display the condition(s) that must be met to obtain the outcome.

NCA was conducted on SmartPLS to provide a thorough output. In the current study, the exogenous constructs were SC ambidexterity and SCAC, while the endogenous constructs were DC and SC sustainability. In the first step, DC was taken as the endogenous variable. Results from the partial regression were first examined. All "VIF" values were below the 3.3 threshold. Additionally, the value of R^2 for DC, which was also assessed in the structural model evaluation, was 0.558 (Table 9). A similar procedure was adopted while considering SC sustainability as the endogenous variable and all "VIF" values were less than the permissible limit [124] with an R^2 value of 0.181.

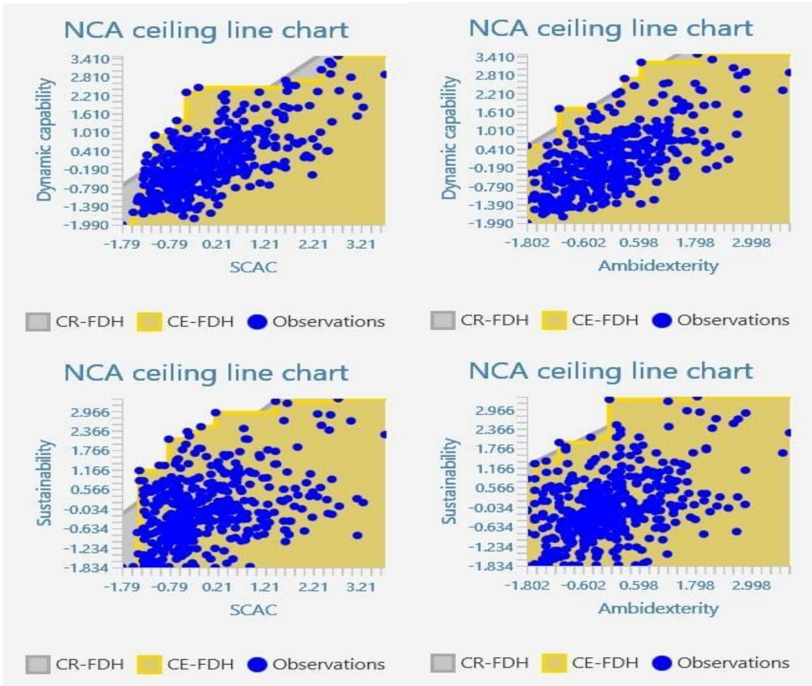

Figure 3. Scatter plots of dynamic capability and SC sustainability from the NCA.

NCA is a valuable method for identifying the specific factors or conditions that are essential for achieving a desired outcome. Through data analysis, researchers can gain a deeper understanding of the causal factors that influence the outcome of interest. NCA not only reveals the key factors that must be addressed or fulfilled to enhance the likelihood of achieving the desired outcome, but it also helps identify potential barriers or obstacles that may impede its attainment. By uncovering these necessary conditions, organizations can focus their efforts on addressing them and developing strategies to overcome any obstacles that may arise. The NCA's results, obtained through NCA permutation (see Table 10), indicate that SC ambidexterity and SCAC are meaningful and significant necessary conditions for resilience. Both variables had a medium effect size according to the criteria given by [122]. In a similar way, SC ambidexterity and SCAC are meaningful and significant necessary conditions for SC sustainability and had a medium size effect. These results also validate the findings of PLSpredict.

Table 10. The NCA effect sizes.

Exogenous Variables	Original Effect Size	95.00%	Permutation *p*-Value
	Endogenous variable = Dynamic capability		
Ambidexterity	0.163	0.077	0.000
SCAC	0.251	0.099	0.000
	Endogenous variable = Supply chain sustainability		
Ambidexterity	0.105	0.073	0.000
SCAC	0.170	0.096	0.000

The bottleneck tables enable a thorough analysis of each necessary condition. For example, Table 11 indicates that to obtain an 80% level of DC, two necessary conditions are needed: ambidexterity at no less than 69.55%, and SCAC at no less than 51.52%. Additionally, to achieve 80% SC sustainability, two necessary conditions must be met: ambidexterity at no less than 51.52%, and SCAC at no less than 42.38%.

Table 11. Bottleneck table (percentages).

	Endogenous variable = Dynamic capability		
	Dynamic capability	**Ambidexterity**	**SCAC**
0.00%	−1.99	0	0
10.00%	−1.443	0	0.468
20.00%	−0.896	0	1.639
30.00%	−0.349	0	3.981
40.00%	0.198	0	5.386
50.00%	0.745	13.115	9.836
60.00%	1.293	13.115	28.571
70.00%	1.84	54.333	40.515
80.00%	2.387	69.555	51.522
90.00%	2.934	77.049	96.721
100.00%	3.481	94.614	98.361
	Endogenous variable = SC sustainability		
	SC sustainability	**Ambidexterity**	**SCAC**
0.00%	−1.834	0	0
10.00%	−1.316	0	0.468
20.00%	−0.798	0	0.468
30.00%	−0.28	0	0.937
40.00%	0.238	0	0.937
50.00%	0.757	0	0.937
60.00%	1.275	1.171	12.881
70.00%	1.793	12.881	20.375
80.00%	2.311	51.522	42.389
90.00%	2.829	51.522	63.7

5.4. Model Robustness

5.4.1. Nonlinear Effects

Exploring the nonlinear effects in data analysis allows for a more precise depiction of the intricate relationships between variables. By incorporating nonlinear terms into the model, it is possible to capture curvilinear patterns and interaction effects that may go unnoticed in linear models. Consequently, this approach provides a deeper and more nuanced understanding of the relationships among variables, leading to enhanced predictive and explanatory capabilities of the model. The method developed by [125] was used to look for probable nonlinearities in the relationships. To evaluate the nonlinear effects in the relationships in [126], the regression equation specification error test (RESET) was used. The input for the RESET test was obtained from the construct score of SmartPLS [124]. The "lmtest" package was used in "R-Studio" to run the RESET test. First, the bootstrapping method in SmartPLS was used to analyze the quadratic effects of ambidexterity and SCAC on DC and SC sustainability. As can be seen in Table 12, no nonlinear effects were found to be significant. Similar to that, the impact of ambidexterity and SCAC on SC sustainability was evaluated using RESET, and no significant nonlinearities in the relationships were observed (RESET = 0.2943, p-value = 0.8817). Furthermore, there was no nonlinear effect of ambidexterity and SCAC on DC (RESET = 0.0147, p-value = 0.9996). As a result, the linear effects model can be said to be robust. The link for the code used in R-studio is located at (https://github.com/Adeelmunir158/SEMinR_Sustainability/blob/main/RAMSAY.R, (accessed on 1 June 2023)).

Table 12. Assessment of nonlinear relations.

Nonlinear Relationship	Path Coefficient	*p*-Value	Ramsey's RESET
(Ambidexterity) → Dynamic capability	0.005	0.812	RESET = 0.0147, *p*-value = 0.9996
(SCAC) → Dynamic capability	0.002	0.926	
(Ambidexterity) → SCAC	0.054	0.067	
(Ambidexterity) → SC sustainability	0.022	0.475	RESET = 0.2943, *p*-value = 0.8817
(SCAC) → SC sustainability	−0.009	0.809	

5.4.2. Endogeneity

Endogeneity must be considered when applying regression-based methods [127]. Endogeneity occurs when the dependent variable and its error are both explained by the predictor construct. Neglecting to address endogeneity in the analysis can result in inaccurate parameter estimates and misleading conclusions. Taking measures to account for endogeneity helps mitigate biases and ensures that the estimated relationships reflect a more reliable and trustworthy representation of causality [128,129]. The Gaussian copula (GC) methodology [130] was employed to investigate probable endogeneity following the methodical procedure given by [127]. The GC methodology is utilized to model the joint distribution of endogenous variables and instrumental variables, which are employed to tackle endogeneity. By specifying the copula function and estimating its parameters, the dependence structure between these variables can be captured effectively. It provides flexibility, robustness, and reliable parameter estimates, contributing to a more accurate understanding of the relationships under investigation. The GC technique was employed using SmartPLS and the results in Table 13 show that none of the GC combinations were determined to be statistically significant. As a result, it can be said that this model had no endogeneity, supporting its robustness [127,131].

Table 13. Assessment of endogeneity.

Test	Constructs	Coefficient	*p*-Values
GC of model 1 (endogenous variables; ambidexterity)	Ambidexterity → Dynamic capability	0.410	0.056
	SCAC → Dynamic capability	0.489	0.000
	GC (Ambidexterity) → Dynamic capability	−0.073	0.727
GC of model 2 (endogenous variables; SCAC)	Ambidexterity → Dynamic capability	0.339	0.000
	SCAC → Dynamic capability	0.463	0.000
	GC (SCAC) → Dynamic capability	0.030	0.808
GC of model 3 (endogenous variables; ambidexterity, SCAC)	Ambidexterity → Dynamic capability	0.443	0.070
	SCAC → Dynamic capability	0.435	0.004
	GC (SCAC) → Dynamic capability	0.057	0.691
	GC (Ambidexterity) → Dynamic capability	−0.109	0.655
GC of model 4 (endogenous variables; ambidexterity)	Ambidexterity → Sustainability	0.457	0.122
	SCAC → Sustainability	0.179	0.001
	GC (Ambidexterity) → Sustainability	−0.174	0.563
GC of model 5 (endogenous variables; SCAC)	Ambidexterity → Sustainability	0.286	0.000
	SCAC → Sustainability	0.132	0.478
	GC (SCAC) → Sustainability	0.054	0.771
GC of model 6 (endogenous variables; ambidexterity, SCAC)	Ambidexterity → Sustainability	0.523	0.088
	SCAC → Sustainability	0.069	0.719
	GC (SCAC) → Sustainability	0.117	0.552
	GC (Ambidexterity) → Sustainability	−0.247	0.435

Abbreviation: GC, Gaussian copula; SCAC, supply chain analytics capability.

5.4.3. Unobserved Heterogeneity

Unobserved heterogeneity refers to hidden characteristics or factors that influence the observed data patterns but are not directly captured by available variables. It introduces additional complexity and variability that need to be considered in statistical analysis and modeling. Ignoring unobserved heterogeneity can lead to biased or misleading results, as the full picture of the underlying relationships may not be captured. Accounting for unobserved heterogeneity enhances the validity and reliability of the analysis, enabling a more accurate understanding of the phenomena being studied. To find and manage unobserved heterogeneity, the authors of [111] proposed a methodical strategy that integrated latent class approaches. FIMIX-PLS is predominantly beneficial in this context because it provides the criteria for model selection, which directs the conclusion about the number of data segments to be retained [132,133]. The FIMIX-PLS algorithm begins with initializing the latent class parameters and fuzzy membership using the initial values. Then, it iteratively updates these parameters using the expectation-maximization algorithm. The estimation process continues until the convergence criteria are satisfied such as reaching a maximum number of iterations or a specific threshold for parameter change. According to the results of the "G*Power" software 3.1.9.4, a minimum sample size of 45 is required to extract up to 10 segments, with an effect size of 0.15 and an 80% power level. FIMIX-PLS is run from one to ten segments. The results of the fit indices present a complex picture, as shown in Table A7 in Appendix G. The AIC3 was not in the same segment as that of CAIC and BIC. The performance of AIC4 and BIC in calculating the number of segments in FIMIX-PLS is usually regarded as good, but they are also not in the same segment. Considering the EN requirement, which states that the value should be greater than 0.5, a two-segment solution was reached [132,134]. Table 14 compares the unobserved heterogeneity based on partition 1 (62.5%) and partition 2 (37.4%) with the observed heterogeneity based on the experience of professionals. Here, two groups of observed heterogeneity were formed, one with more than 10 years of experience (39.4%) and the second having experience of less than 10 years (60.6%). There were some interesting observations as for unobserved heterogeneity: one group of professionals supported the effect of ambidexterity and SCAC on dynamic capability (DC) as well as SC sustainability, but the other group differed in its opinion as they considered that ambidexterity and SCAC had a significant effect on DC, but not on sustainability. Similar trends were observed for observed heterogeneity as professionals with experience >10 years also considered that SCAC had no significant impact on SC sustainability.

Table 14. Comparison of unobserved heterogeneity and observed heterogeneity.

	Complete Sample		**Partition-1**		**Partition-2**		**Experience > 10 Years**		**Experience < 10 Years**	
	Coeff	***p*-Value**	**Coeff**	***p*-Value**	**Coeff**	***p*-Value**	**Coeff**	***p*-Value**	**Coeff**	***p*-Value**
Ambidexterity → Dynamic capability	0.340	0.000	0.324	0.000	0.301	0.000	0.290	0.000	0.347	0.000
SCAC → Dynamic capability	0.490	0.000	0.471	0.000	0.553	0.000	0.560	0.000	0.467	0.000
Ambidexterity → SC sustainability	0.289	0.000	0.202	0.090	0.483	0.000	0.223	0.000	0.333	0.000
SCAC → SC sustainability	0.182	0.000	−0.08	0.403	0.387	0.000	0.146	0.181	0.223	0.001
Reliability and validity										
Cronbach's alpha	✓		✓		✓		✓		✓	
Composite reliability	✓		✓		✓		✓		✓	
AVE	✓		✓		✓		✓		✓	
R-Square										
Dynamic capability	0.558		0.466		0.700		0.630		0.517	
SC sustainability	0.180		0.032		0.723		0.118		0.242	
SCAC	0.370		0.207		0.830		0.509		0.303	

Abbreviation: SCAC, supply chain analytics capability; Coeff, coefficient.

5.4.4. Measurement Invariance of Composites (MICOM)

If the invariance of the researchers' measures is not proven, group comparisons in structural equation modeling (SEM) may be misleading [135]. Data were gathered for this study from three countries, the majority of whom were from Pakistan (209). The remaining responders (218) were from Bangladesh and India. Thus, based on the categorical variable "country's name", two groups were formed. One set was for the Pakistani respondents, and the other was for the Indian and Bangladeshi respondents. The next step was to assess the measurement invariance. The authors in [114] developed the MICOM procedure, which incorporates the assessment in three parts. The evaluation of configural invariance is the initial stage, and the research model satisfies this requirement. The second phase involves evaluating the compositional invariance using permutation multigroup analysis using SmarPLS. The outcome shows that (Appendix H, Table A8) all permutation *p*-values were significant, so compositional invariance was established. For the following phase (Appendix H, Table A8), when the mean and variance of all the constructs in each group were compared, no significant differences were found. Therefore, it was proven that there is complete measurement invariance and that the data from both groups may be pooled [114]. Table 15 shows the outcomes of the bootstrap multigroup analysis (MGA) that was carried out for additional validation.

Table 15. Bootstrapping results of MICOM.

	Original (Group_India and Bangladesh)	*p*-Value (Group_India and Bangladesh)	Original (Group_Pakistan)	*p*-Value (Group_Pakistan)	Invariant
Ambidexterity → Dynamic capability	0.354	0.000	0.329	0.000	yes
Ambidexterity → SCAC	0.670	0.000	0.533	0.000	yes
Ambidexterity → Sustainability	0.293	0.000	0.281	0.000	yes
SCAC → Dynamic capability	0.491	0.000	0.485	0.000	yes
SCAC → Sustainability	0.167	0.040	0.205	0.008	yes

6. Discussion and Implications

SCs are frequently using new inventive and transformative techniques to improve sustainability and dynamic capabilities (DCs). Based on the statistical analysis, the empirical results present an intriguing picture that adds to the existing knowledge about the complicated interaction between sustainability, DC, and SC ambidexterity with the mediating effect of SCAC. The results of this study demonstrated that ambidexterity is certainly associated with company performance in terms of agility and sustainability, which is in consistent with the existing empirical evidence [20,136,137]. Ambidexterity is necessary to effectively and flexibly reconcile exploitation and exploration, considering the level of environmental dynamism and a technology-focused position. Moreover, SCAC is all about combining resources, technology, and personnel capabilities for effective decision-making and to improve the sustainable performance of the firm. SCAC provides firms with so much information that it can improve their capacity to sense the opportunities or threats, restructure their resources accordingly, and then react in any kind of uncertain situation. It might be concluded that this study adds some valuable information regarding managerial and theoretical implications.

6.1. Theoretical Implications

Using DCV, this research links the ambidexterity and data analytics capability with the sustainability and DC of the firm. Exploration and exploitation are two opposite characteristics of ambidexterity in a firm, while DC and sustainability are two separate notions that coexist in ambidextrous firms.

The first addition this study makes is that it provides guidelines to develop DC in the SC. DCs are not innate and can be improved by a well-functioning organizational process for success over the long-term [56]. Through a review of the literature, this study recommends that organizations should improve their visibility, agility, and adaptability in order to build DC along the SC [20]. Second, the findings of the study demonstrate that the development of SC ambidexterity is preceded by a DC building process. In earlier research, emphasis was predominantly given to the effects of ambidexterity on firm performance, new product development, and competitive edge [9,25,32]. This study revealed that a key factor in enhancing SCAG is the capacity to efficiently use currently available resources, along with developing unique solutions for problems and seeking opportunities along the SC. Third, this study expands the existing knowledge concerning organizational SCAC and a firm's success by examining how ambidexterity and agility might assist organizations to obtain valuable information from the SC data that they can utilize for performance improvement [12,15]. This research proposes a mediation model that can be used to comprehend the intricate dynamics and relationships of ambidexterity, SCAC, and DCs. Fourth, this study provides empirical validation that SCAC and ambidexterity in the organization's SC can be used to restore its social, economic, and environmental vitality to the community. This result also accords with a few earlier studies that discovered that SCAC has an impact on ambidexterity and agility in improving economic and organizational performance [25,63,65,138]. However, it may be concluded through thorough analysis of model robustness that SCAC and SC ambidexterity have a larger impact on DC compared to sustainability. Exploitation of the current resources and exploring the innovative ones improve the organizations' SC agility, providing them with a better ability to redeploy resources to quickly meet varying demands. The coexistence of exploitation and exploration is essential for achieving sustainability while maintaining profitability, resulting in better and sustainable performance throughout the SC [139].

6.2. Managerial Implications

In addition to having theoretical aspects, this study's findings can help practitioners and SC managers who are considering investing in SCAC to achieve improved DCs and sustainable performance throughout the SC. By empirically validating the theoretical model, there is solid evidence that firms do really benefit from SCAC to sense, seize, and respond to market fluctuations. The study also provides guidance to SC managers and human resource managers on how developing these abilities might give the firm a sustainable competitive advantage. The SC partners pursuing sustainable performance should benefit from the study's greater insights into the role of SCAC in speeding up digital transformation throughout the SC and strengthening SC ambidexterity. Furthermore, the research findings support the notion that managers can anticipate their firms acquiring a competitive edge over rivals by exploiting the innovative technology in attempts to enhance SCAC. Despite the SCAC increasing the agility and sustainability of ambidextrous organizations, organizations encounter several difficulties when managing huge amounts of data.

Firms must create an architecture made up of several databases, processors, and devices in order to make use of the important information derived from the SC raw data [140]. Second, a firm might need to invest in nested computer networks that can manage numerous data types simultaneously. These features allow businesses to collect, categorize, retain, and analyze data that is kept in their repositories [141]. These technical frameworks must be adaptable enough to change along with the organizational structure. However, the complexity of the SC data cannot be handled by technology alone. Organizations must spend a lot of money on the training of professionals [15]. The organizations' data analysts must be knowledgeable in a variety of software, model building, network analysis, clustering, data classification, and artificial intelligence techniques. The challenges of SC data analysis can therefore not just be overcome by employee training alone, but also by changing the organization's culture to one that is data-driven [48].

Despite these challenges, an ambidextrous organization could put these mechanisms in place, giving managers a meaningful overview of the consumer's information. This would provide agile organizations with a clear competitive advantage because it would allow them to obtain facts about any product or service an organization desires to improve. Organizations aiming to combine agility and sustainability with data analytics capability will be required to extend beyond their current frame of mind and aspire to exploration and transformation, thus a culture shift is a crucial factor to consider.

7. Conclusions

The relationship between SCAC, ambidexterity, DC, and sustainability in the SC has received a lot of attention in the literature because SCs are under pressure to secure the sustainability of their operations and their urgent need to improve agility. This study's primary objective was to investigate the function of SC ambidexterity to enhance the dynamic capability of SC, which consists of visibility, agility, and adaptability as well as SC sustainability, which includes economic, environmental, and social performance. This study also examined the SCAC's role as a mediator between ambidexterity and sustainability as well as dynamic capability. Regarding its practical inferences, this research demonstrates the significance of SCAC in increasing the agility of ambidextrous organization, particularly for businesses that deal with a large amount of data on a regular basis.

The findings demonstrate a significant positive relationship between SC ambidexterity and sustainability as well as with dynamic capability. Additionally, between SC ambidexterity and SC sustainability as well as between SC ambidexterity and dynamic capability, SCAC has a complementary partial mediating role. In comparison to previous studies, the impacts of ambidexterity on SC sustainability and SC dynamic capacities were simultaneously examined and empirically evaluated in this research. An extensive literature review was conducted to measure the dynamic capability through market sensing ability, SC agility, and reconfigurability. We considered how different dynamic SC capabilities interacted with one another and how this interaction affected the SC's overall performance. Together, these DC clusters enable organizations to adjust their SCs in response to both short- and long-term market demands. Additionally, this research also sought to ascertain the link between ambidexterity and SC sustainability as well as the effect of SCAC on the triple-bottom-line of SC sustainability.

It is critical to assess the results of a study and its contributions in light of its limitations. The following limitations of this study can be addressed in future research. First, the respondents in this study were from three South Asian countries with underdeveloped data analytics capabilities. As a result, the respondents' familiarity with the methodologies under investigation may have been a problem. Second, this study evaluated the model using cross-sectional data, therefore, its conclusions should not be interpreted as definitive evidence of any underlying relationships. Only longitudinal research can provide definite evidence. Third, one shortcoming of this study is the existence of the observed and unobserved heterogeneity in the data, as assessed through FIMIX-PLS. The factors that led to a poorer outcome might be validated by using a different sample size in a different region. Fourth, because the scope of this study was restricted to product-based organizations in three South Asian countries, testing the model on different types of SCs in other countries would help to clarify how these variables relate to one another. Finally, any study that employs a methodology based on surveys faces a generalizability issue. Finding a sample that can be said to be accurately representative of the entire population is exceedingly challenging. In fact, it is recommended that future scholars compare various marketplaces and industries while thoroughly examining case studies from different organizations. Despite these drawbacks, the study presented some valuable insights. The findings emphasize how SCAC and ambidexterity help firms become more dynamic and responsive to external changes, which in turn increases the organizational agility and sustainability.

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Appendix A

Table A1. Construct operationalization.

Constructs	Relevant Literature		Measures
Supply chain analytics capability (SCAC)			
Technical capability	[60,64,65,142]	TC1	Our company has the capacity to gather, consolidate, and integrate data from all sources for efficient supply chain decision-making.
		TC2	Our company employs very advanced analytical methodologies to significantly improve the supply chain process.
		TC3	For a better understanding of complex information, our company employs data visualization approaches.
Management capability	[5,10,17,28]	MC1	In our organization, information is extensively shared among front-line employees for responsible decision-making.
		MC2	The managers at our company are capable of understanding and evaluating the outcomes of large volumes of data.
		MC3	Using supply chain data, our company's management may foresee impending business requirements from managers, suppliers, and consumers.
Human resource capability	[17,27,65]	HC1	Our company's data analytics team is exceptionally skilled at managing data effectively.
		HC2	Our data analytics team can efficiently analyze supply chain data and use the results for effective decision-making.
		HC3	Our data analytics team closely collaborates with customers and suppliers to gather information that might assist in more informed decision-making.
Data-driven culture	[58,62,65,143]	DD1	Making decisions based on data is inherent in our company's culture.
		DD2	Our staff members are constantly willing to adapt their opinions in light of new information.
		DD3	Our company frequently assesses and modifies its business plans in reaction to the data observations.
Supply chain ambidexterity			
Exploitative capability	[20,65,72,144,145]	Exploit1	To build strong competence in the existing system, it is part of our organization's plan to upgrade the current technology.
		Exploit2	Our firm uses cutting-edge tools and methods to enhance current supply chain procedures.
		Exploit3	To satisfy the demands of existing consumers, our organization's managers are concentrated on reducing operational expenses.
		Exploit4	To better meet the consumer needs, our company implements even minor upgrades in current technology, products, and services.
Explorative capability	[51,64,72,144–147]	Explore1	The philosophy of our company is to constantly research and apply fresh perspectives and cutting-edge techniques to enhance organizational operations.
		Explore2	Our company's strategy is to accept requests for products and services that are far beyond what we now offer in order to serve new customers and markets.
		Explore3	Our company regularly conducts analysis to assess problems and their solutions to enhance the supply chain infrastructure.
		Explore4	Our organization constantly looks for and takes advantage of new opportunities to address supply chain issues.

Table A1. *Cont.*

Constructs	Relevant Literature		Measures
Dynamic capability			
SC visibility	[17–19,21,25,30,64]	Vis1 (Deleted)	Our company has the capacity to recognize significant changes in its surroundings promptly.
		Vis2	Our company has the ability to identify the risks and threats in its surroundings very rapidly.
		Vis3	Our organizations collect information from customers and suppliers and regularly shares it with the whole supply network.
		Vis4	Our company has successfully built "information sharing platforms" with all of the supply chain partners as well as within the company.
SC agility	[17–19,21,25,30,64]	Agile1	Our organization's supply chain can remain in a steady state for a considerable amount of time.
		Agile2	Our supply chain can function for a very long time, giving us plenty of time to make necessary adjustments after some fluctuation in the supply or demand of products.
		Agile3	For raw materials and spare parts, our company always has a backup plan.
		Agile4 (Deleted)	Through its strong business partnerships, our company has access to all of the essential resources accessible in the market including information, skills, and technologies.
		Agile5	In order to ensure the efficient flow of commodities and information, our organization has effectively built partnerships with all of our supply chain partners.
		Agile6	Our company consistently maintains a stock of finished goods to increase responsiveness to shifting market demands.
SC adaptability	[22,31,66,79,148]	Adapt1	Our company employs multiskilled workers to meet the various consumer requests.
		Adapt 2	Our company's supply chain can operate effectively under a variety of circumstances such as a sudden change in product demand or variable manufacturing timetables.
		Adapt 3	Our business can successfully restructure supply chain resources swiftly in reaction to an unexpected market change.
		Adapt 4	Any form of supply chain turbulence can be quickly resolved by our firm, allowing operations to return to normal.
		Adapt 5 (Deleted)	For logistical challenges such as transportation challenges, deteriorating road conditions, and fleet utilization, our team prepares alternative alternatives.
Supply chain sustainability			
Economic performance	[10,65,82,149–151]	Econ1	The market share of our organization has been continuously increasing for the last three years.
		Econ2	Our organization's profit has increased significantly during the last three years.
		Econ3	Energy consumption performance of the supply chain of our company and its major suppliers has been increased.
		Econ4	To reduce inventory and increase product quality, we facilitate our suppliers in applying total quality management practices in the supply chain.
		Econ5	The managers of our organization are concentrated on reducing supply chain operational costs to provide good services to customers at the optimum cost.
Environmental performance	[5,6,10,27,65,82, 149–152]	Environ1	Our organization's supply chain has increased its level of compliance against environmental standards (local policies and ISO standards).
		Environ2	Our organization and its suppliers have taken necessary precautions to avoid solid waste discharge.
		Environ3	Our organization and its suppliers' environmental performance has improved in terms of air pollution reduction.
		Environ4	Our organization and its suppliers' environmental performance has increased in terms of water conservation.
		Environ5	We have successfully designed our products that consume a reduced amount of input materials/energy.

Table A1. *Cont.*

Constructs	Relevant Literature		Measures
Social Performance	[5,6,10,27,41,65,82,149–154]	Soc1	Our firm has a strong reputation for being trustworthy among all supply chain partners.
		Soc2	Our organization and its suppliers place health and safety of all employees on high priority.
		Soc3	Our organization and its suppliers provide extensive education and training opportunities to their employees.
		Soc4	Our organization and its suppliers are dedicated to adapting all strategies to prevent any kind of discrimination based on gender, color, religion, and ethnicity, etc.
		Soc5	Our organization and its suppliers pay significant attention to acting against corruption and the violation of human rights (e.g., discrimination, forced, and child labor)

Appendix B

Table A2. Descriptive statistics.

Name	Missing	Mean	Median	Observed Min	Observed Max	Standard Deviation	Excess Kurtosis	Skewness	Cramér–von Mises *p*-Value
Country	0								
Experience	0								
Industry	0								
Firm size	0								
TC1	0	1.95	2	1	5	0.79	0.99	0.85	0.000
TC2	0	2.39	2	1	5	1.05	−0.58	0.45	0.000
TC3	0	2.26	2	1	5	0.94	−0.32	0.55	0.000
MC1	0	2.16	2	1	5	0.93	0.08	0.74	0.000
MC2	0	2.07	2	1	5	0.85	0.40	0.75	0.000
MC3	0	2.06	2	1	4	0.83	0.10	0.64	0.000
HC1	0	2.01	2	1	5	0.90	0.54	0.87	0.000
HC2	0	2.01	2	1	5	0.99	1.37	1.18	0.000
HC3	0	2.14	2	1	5	1.00	−0.26	0.56	0.000
DD1	0	2.06	2	1	5	0.88	0.42	0.79	0.000
DD2	0	2.15	2	1	5	0.87	0.20	0.66	0.000
DD3	0	2.17	2	1	5	0.90	1.95	1.22	0.000
Exploit1	0	1.80	2	1	4	0.64	0.33	0.42	0.000
Exploit2	0	2.00	2	1	4	0.76	0.38	0.63	0.000
Exploit3	0	1.89	2	1	5	0.73	1.71	0.94	0.000
Exploit4	0	1.88	2	1	4	0.69	0.39	0.51	0.000
Explore1	0	1.95	2	1	5	0.77	1.34	0.89	0.000
Explore2	0	1.95	2	1	5	0.82	0.23	0.70	0.000
Explore3	0	2.03	2	1	5	0.84	0.70	0.80	0.000
Explore4	0	2.12	2	1	5	0.85	2.30	1.20	0.000
Visibility1	0	2.34	2	1	5	0.96	−0.28	0.54	0.000
Visibility2	0	1.95	2	1	5	0.98	0.21	0.89	0.000
Visibility3	0	2.13	2	1	5	0.83	0.24	0.65	0.000
Visibility4	0	2.25	2	1	5	0.90	−0.01	0.63	0.000
Agility1	0	1.82	2	1	5	0.90	1.66	1.32	0.000
Agility2	0	1.91	2	1	5	0.82	0.82	0.92	0.000
Agility3	0	1.96	2	1	4	0.79	0.22	0.65	0.000
Agility4	0	2.31	2	1	4	0.91	−0.49	0.52	0.000
Agility5	0	1.90	2	1	4	0.75	0.71	0.77	0.000
Agility6	0	2.01	2	1	4	0.74	0.89	0.77	0.000
Adapt1	0	2.10	2	1	5	0.76	1.29	0.88	0.000
Adapt2	0	2.13	2	1	4	0.89	−0.14	0.67	0.000
Adapt3	0	2.01	2	1	4	0.81	0.34	0.73	0.000

Table A2. *Cont.*

Name	Missing	Mean	Median	Observed Min	Observed Max	Standard Deviation	Excess Kurtosis	Skewness	Cramér–von Mises p-Value
Adapt4	0	2.02	2	1	4	0.72	1.24	0.82	0.000
Adapt5	0	1.74	2	1	4	0.76	0.40	0.86	0.000
Econom1	0	2.05	2	1	4	0.76	0.01	0.44	0.000
Econom2	0	2.18	2	1	4	0.80	−0.32	0.32	0.000
Econom3	0	2.22	2	1	4	0.79	0.05	0.53	0.000
Econom4	0	2.21	2	1	4	0.80	0.04	0.54	0.000
Econom5	0	1.94	2	1	4	0.70	1.11	0.73	0.000
Environ1	0	1.90	2	1	5	0.87	1.71	1.15	0.000
Environ2	0	2.09	2	1	5	0.95	0.47	0.84	0.000
Environ3	0	2.12	2	1	5	0.88	0.14	0.60	0.000
Environ4	0	2.19	2	1	5	0.87	0.13	0.59	0.000
Environ5	0	2.07	2	1	5	1.03	0.19	0.82	0.000
Social1	0	1.76	2	1	5	0.73	1.46	0.98	0.000
Social2	0	1.90	2	1	5	0.89	1.02	1.04	0.000
Social3	0	2.15	2	1	5	0.98	0.59	0.89	0.000
Social4	0	1.88	2	1	5	0.81	0.98	0.91	0.000
Social5	0	1.77	2	1	5	0.82	1.21	1.10	0.000

Appendix C

Table A3. Paired samples statistics for non-response bias.

	Variables	Mean	N	Std. Deviation	Paired Difference of Mean	t-Statistics	Sig. (2-Tailed)
Pair 1	Adaptability_Early Adaptability_Late	0.130 −0.047	100 100	1.0713 0.9485	0.177	1.306	0.195
Pair 2	Agility_Early Agility_Late	0.186 0.084	100 100	1.1104 0.9524	0.102	0.702	0.484
Pair 3	Data driven_Early Data driven_Late	0.146 −0.055	100 100	1.1668 0.9488	0.201	1.353	0.179
Pair 4	Economic_Early Economic_Late	−0.212 0.071	100 100	1.1501 0.9271	−0.283	−1.911	0.059
Pair 5	Environmental_Early Environmental_Late	−0.077 0.059	100 100	1.0470 1.0224	−0.136	−0.912	0.364
Pair 6	Exploitative_Early Exploitative_Late	0.087 −0.033	100 100	1.1076 0.9286	0.120	0.868	0.388
Pair 7	Explorative_Early Explorative_Late	0.095 0.001	100 100	1.1373 0.9369	0.094	0.688	0.493
Pair 8	Human resource_Early Human resource_Late	0.154 0.008	100 100	1.0813 0.9270	0.146	0.991	0.324
Pair 9	Management_Early Management_Late	0.136 0.013	100 100	1.1065 1.0450	0.123	0.849	0.398
Pair 10	Social_Early Social_Late	0.090 0.052	100 100	1.0560 0.8882	0.038	0.289	0.773
Pair 11	Technical_Early Technical_Late	0.167 0.002	100 100	1.0908 0.9636	0.166	1.128	0.262
Pair 12	Visibility_Early Visibility_Late	0.038 0.016	100 100	1.1134 0.9758	0.023	0.145	0.885

Appendix D

Table A4. Common method biasness test with marker variable.

	Beta Coefficient	T Statistics	p-Values
Marker → Ambidexterity	−0.048	0.958	0.338
Marker → Dynamic capability	−0.051	1.510	0.131

Table A4. *Cont.*

	Beta Coefficient	T Statistics	*p*-Values
Marker → SCAC	−0.017	0.456	0.648
Marker → Sustainability	−0.004	0.100	0.920

Appendix E

Table A5. Kolmogorov–Smirnov test of normality for prediction errors.

Construct Items	Statistic	df	Sig.
Adapt1	0.109	4270	0.000
Adapt2	0.083	4270	0.000
Adapt3	0.055	4270	0.000
Adapt4	0.098	4270	0.000
Agility1	0.110	4270	0.000
Agility2	0.090	4270	0.000
Agility3	0.072	4270	0.000
Agility5	0.054	4270	0.000
Agility6	0.099	4270	0.000
DD1	0.094	4270	0.000
DD2	0.095	4270	0.000
DD3	0.086	4270	0.000
Econom1	0.086	4270	0.000
Econom2	0.088	4270	0.000
Econom3	0.121	4270	0.000
Econom4	0.130	4270	0.000
Econom5	0.089	4270	0.000
Environ1	0.122	4270	0.000
Environ2	0.111	4270	0.000
Environ3	0.109	4270	0.000
Environ4	0.134	4270	0.000
Environ5	0.130	4270	0.000
HC1	0.083	4270	0.000
HC2	0.076	4270	0.000
HC3	0.083	4270	0.000
MC1	0.084	4270	0.000
MC2	0.067	4270	0.000
MC3	0.074	4270	0.000
Social1	0.126	4270	0.000
Social2	0.107	4270	0.000
Social3	0.120	4270	0.000
Social4	0.121	4270	0.000
Social5	0.118	4270	0.000
TC1	0.085	4270	0.000
TC2	0.068	4270	0.000
TC3	0.085	4270	0.000
Visibility2	0.064	4270	0.000
Visibility3	0.065	4270	0.000
Visibility4	0.098	4270	0.000

Appendix F

Table A6. PLSpredict assessment of the dependent manifest variables.

	Q^2 Predict	PLS-SEM_MAE	LM_MAE	(PLS-SEM_MAE)-(LM_MAE)
Adapt1	0.145	0.513	0.527	−0.014
Adapt2	0.092	0.656	0.66	−0.004
Adapt3	0.114	0.593	0.593	0
Adapt4	0.278	0.45	0.463	−0.013

Table A6. *Cont.*

	Q^2 Predict	PLS-SEM_MAE	LM_MAE	(PLS-SEM_MAE)-(LM_MAE)
Agility1	0.11	0.636	0.643	−0.007
Agility2	0.106	0.578	0.571	0.007
Agility3	0.119	0.564	0.567	−0.003
Agility5	0.168	0.528	0.539	−0.011
Agility6	0.216	0.482	0.5	−0.018
DD1	0.2	0.608	0.615	−0.007
DD2	0.214	0.589	0.599	−0.01
DD3	0.06	0.634	0.619	0.015
Econom1	0.046	0.568	0.567	0.001
Econom2	0.011	0.634	0.634	0
Econom3	0.034	0.603	0.604	−0.001
Econom4	0.031	0.605	0.613	−0.008
Econom5	0.212	0.459	0.402	0.057
Environ1	0.064	0.623	0.637	−0.014
Environ2	0.042	0.71	0.717	−0.007
Environ3	0.044	0.677	0.687	−0.01
Environ4	0.048	0.664	0.672	−0.008
Environ5	0.019	0.803	0.818	−0.015
HC1	0.16	0.626	0.636	−0.01
HC2	0.087	0.732	0.729	0.003
HC3	0.112	0.767	0.782	−0.015
MC1	0.181	0.654	0.656	−0.002
MC2	0.238	0.561	0.568	−0.007
MC3	0.219	0.557	0.565	−0.008
Social1	0.068	0.561	0.567	−0.006
Social2	0.031	0.667	0.669	−0.002
Social3	0.054	0.722	0.736	−0.014
Social4	0.025	0.599	0.599	0
Social5	0.053	0.626	0.628	−0.002
TC1	0.135	0.564	0.57	−0.006
TC2	0.185	0.749	0.751	−0.002
TC3	0.196	0.664	0.67	−0.006
Visibility2	0.091	0.759	0.766	−0.007
Visibility3	0.164	0.585	0.589	−0.004
Visibility4	0.213	0.624	0.632	−0.008

Appendix G

Table A7. Fit indices for the one to ten segment solutions.

	No of Segments									
Criteria	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
AIC	10,836	10,543	10,356	10,319	10,263	10,117	10,159	10,065	9968	**9926**
AIC3	10,899	10,670	10,547	10,574	10,582	**10,500**	10,606	10,576	10,543	10,565
AIC4	10,962	10,797	**10,738**	10,829	10,901	10,883	11,053	11,087	11,118	11,204
BIC	11,092	**11,058**	11,131	11,353	11,557	11,671	11,972	12,138	12,301	12,518
CAIC	**11,155**	11,185	11,322	11,608	11,876	12,054	12,419	12,649	12,876	13,157
HQ	10,937	10,746	**10,662**	10,727	10,774	10,731	10,875	10,884	10,889	10,950
MDL5	**12,618**	14,135	15,758	17,531	19,286	20,950	22,802	24,518	26,231	27,999
LnL	**−5355**	−5144	−4987	−4904	−4813	−4676	−4632	−4521	−4409	−4324
EN	0.000	0.720	0.710	0.762	0.785	0.833	0.833	0.884	0.877	0.882
NFI	0.000	0.761	0.723	0.753	0.762	0.801	0.797	0.847	0.836	0.839
NEC	0.000	119.5	123.6	101.6	91.7	71.5	71.4	49.4	52.5	50.5

Abbreviations: AIC: Akaike's information criterion; AIC3: modified AIC with factor 3; AIC4: modified AIC with factor 4; BIC: Bayesian information criteria; CAIC: consistent AIC; HQ: Hannan Quinn criterion; MDL5: minimum description length with factor 5; LnL: log likelihood; EN: entropy statistic; NFI: non-fuzzy index; NEC: normalized entropy criterion; numbers in bold indicate the best outcome per segment retention criterion.

Appendix H

Table A8. MICOM result of invariance.

	Original Correlation	Correlation Permutation Mean	5.00%		Permutation p-Value	Compositional Invariance
Ambidexterity	1	0.999	0.998		0.595	yes
Dynamic capability	1	0.999	0.998		0.469	yes
SCAC	1	1	0.999		0.979	yes
Sustainability	0.998	0.997	0.991		0.369	yes
MICOM (Mean)						
	Original Difference	**Permutation Mean Difference**	**5.00%**	**95.00%**	**Permutation p-Value**	**Equal Mean**
Ambidexterity	−0.115	0.005	−0.156	0.164	0.111	yes
Dynamic capability	−0.075	0.006	−0.146	0.164	0.195	yes
SCAC	−0.05	0.002	−0.152	0.16	0.293	yes
Sustainability	−0.097	0.003	−0.16	0.168	0.163	yes
MICOM (Variance)						
	Original Difference	**Permutation Mean Difference**	**5.00%**	**95.00%**	**Permutation p-Value**	**Equal Variance**
Ambidexterity	0.076	0.005	−0.266	0.261	0.334	yes
Dynamic capability	0.046	−0.002	−0.275	0.261	0.379	yes
SCAC	0.243	0.004	−0.266	0.265	0.068	yes
Sustainability	−0.037	−0.001	−0.262	0.275	0.412	yes

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