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From Insights to Action: Big Data Analytics Management Capability as a Moderator for Supply Chain Learning and Agility

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ABSTRACT

Objective: Underpinned by Organizational Information Processing Theory, this study aimed to explore the relationship between Supply Chain Learning, Agility, Adaptability, and Big Data Analytics Management Capability in the context of potential supply chain disruptions.

Methodology: The study population is manufacturing companies in Punjab, Pakistan; the samples are derived using stratified random sampling, with the industry serving as strata.

Results: Our findings confirm that supply chain learning significantly affects supply chain agility and adaptability, with adaptability mediating this relationship. However, while big data analytics management capability significantly moderates the direct relationship between supply chain learning and agility, it does not significantly impact the indirect effect of supply chain learning and agility through supply chain adaptability. This suggests that big data analytics management capability is more crucial in facilitating instant, agile responses than in supporting longer-term strategic adjustments.

Implications: The study enriches the supply chain management discourse by demonstrating the strategic role of big data analytics management capability in enhancing learning and adaptive capabilities within supply chains. Practical implications for managers include the importance of investing in big data analytics management capability to leverage supply chain learning effectively for improved agility while acknowledging that additional strategies may be required to enhance adaptability in response to the evolving landscape of supply chain operations.

Keywords: Big Data Analytics Management Capability, Supply Chain Agility, Supply Chain Learning, Supply Chain Adaptability.

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1. INTRODUCTION

Disruptions to supply chain operations are set to persist globally in 2024 (Marisa, 2024; Tomas *et al*., 2024). These ongoing disruptions pose significant threats to economic stability and adversely affect business performance. Key causes include geopolitical risks, economic and environmental challenges, and technological advancement (Barbarà & Galea, 2024; McCaffrey *et al*., 2023). Geopolitical risks primarily resulting from trade barriers and changes in logistics routes, are considered as major disruptors (Bednarski *et al*., 2023). Economic challenges encompass financial crises, fluctuating market demands, and other variables (Ascari *et al*., 2024). Environmental challenges, notably climate change, also plays a crucial role (Barbarà & Galea, 2024). Additionally, continuous technological advancement is another aspect that calls for regular upgradation, especially to sustain productivity and resilience.

However, to mitigate these disruptions, Supply Chain Agility (SAG), Supply Chain Adaptability (SCAD), and Supply Chain Learning (SCL) remain vital capabilities (Dubey *et al*., 2024; Phadnis, 2024; Zhou *et al*., 2024). These capabilities help maintain operational steadiness and adequately managing dynamic market conditions (Schoenherr, 2023). SAG enables swift responses in supply chains toward customers in a dynamic environment, while SCAD facilitates long-term supply chain changes (Aslam *et al*., 2018). Silvestre *et al*. (2023) entails learning through insights gathered from past disruptions and information throughout the supply chain for better future operations. Nonetheless, the latest technology of Industry 4.0, like BDA, offers the potential to extract meaningful results from immense data. While its dimension of Big Data Analytics Management Capability (BDAMC) plays a crucial role in strategic decisions of big data planning, controlling, and executing (Akter *et al*., 2016), its relationships with SAG and SCAD require more research (Bag *et al*., 2023).

Global and local disruptions have impacted Punjab, Pakistan, particularly due to political instabilities, natural disasters, and resource shortages (Aleha *et al*., 2024), all of these magnify the threats to supply chain resilience (Waseem & Rana, 2023). Hence, addressing it timely is significant as facing continous supply chain disruption would be a disaster for an underdeveloped country like Pakistan, where means are restricted and manufacturing problems are prevalent.

Organizational Information Processing Theory (OIPT) provides a framework to understand how organizations can handle and use information effectively under conditions of uncertainty and complexity (Galbraith, 1974, 1977; Tushman & Nadler, 1978). Within the supply chain management (SCM) context, OIPT is useful in emphasizing the need to balance the information processing activities with the disruptions in the supply chain (Belhadi *et al*., 2024). OITP has been used in past research to test different supply chain aspects, including the effectiveness of supply chain processes, supply chain fit, transparency, and resilience (Belhadi *et al*., 2024; Srinivasan & Swink, 2015).

SCL and SCAD have not been studied in the literature under OITP, despite organizational learning has been studied (Trautmann *et al*., 2009). SAG has also been studied (Dubey *et al*., 2022), and BDAMC has also been viewed as an information-processing capacity (Srinivasan & Swink, 2018). Therefore, connecting these variables through the lens of OIPT, our study argues that effective information processing and utilization are important to avoid disruptions.

Based on the above discussion, the following are the research questions:

R1: How does SCAD serve as a mediator in the relationship between SCL and SAG?

R2: What role does BDAMC play as a moderator in the relationship between SCL and SCAD and SCL and SAG?

2. LITERATURE REVIEW

Organizational Information Processing Theory

The OIPT assumes that organizations are open social systems that require information processing to reduce uncertainty to accomplish their strategic goals (Galbraith, 1974). This theory is fundamental in explaining how firms create their structure and procedures to manage information in an environment of uncertainty and complexity. OIPT consists of three primary components: Information processing requirements, information processing capabilities, and the match between these requirements and capabilities (Tushman & Nadler, 1978).

Information processing requirements are the amount and kind of information required for decision-making and work performance within an organization (Dubey *et al*., 2022). In the context of SCM, these requirements are subject to various forms of internal and external uncertainty (Hult *et al*., 2010). There are two types of uncertainty: endogenous and exogenous. Endogenous uncertainties come from within the supply chain, such as variability in production processes, whereas exogenous uncertainties come from outside the supply chain, such as market risk and geopolitical risk. Identifying and managing these risks is crucial for the sustainability and consistency of supply chain systems.

OIP capabilities refer to the systems and tools that organizations use to acquire, transform, and distribute information (Galbraith, 1974). These capabilities can be improved in several ways, including developing linkages and investing in vertical information systems (Srinivasan & Swink, 2018).

According to OIPT, for organizations to perform optimally, they have to match (Fit) the OIP requirements and capabilities (Galbraith, 1974). This alignment may be done by diminishing the requirement for information through mechanistic structures of the organization or by increasing the organization's information processing capacity (Galbraith, 1977). Mechanistic structures use formal rules, centralized decision-making, and structured processes to coordinate routine activities and minimize uncertainty (Srinivasan & Swink, 2018).

Supply Chain Agility

Supply chain agility (SAG) is a competence that needs to be managed by the firm to be able to adapt promptly to the fluctuations of the market environment (Humdan *et al*., 2023). SAG assists firms in responding to short-term market forces and continues functioning in unstable conditions. Entrepreneurial Agility means the capability of a firm to quickly and efficiently capitalize on opportunities in a given market before rivals do (Eckstein *et al*., 2015). Adaptive Agility also encompasses the process of responding to negative conditions and being able to regain ground after such occurrences (Gligor & Holcomb, 2012). These dimensions of SAG enable firms to be in a position to gain opportunities like "ahead of time and cope with threats." With disruption increasing, SAG is becoming more necessary (Aslam *et al*., 2024).

SCL and SAG

SCL involves the process of assimilating, transferring, and applying information across a firm and its supply chain partners, thereby facilitating continuous improvement and innovation (Bessant *et al*., 2003). This learning goes beyond information acquisition; it involves transforming information into actionable information that can drive strategic decisions and operational improvements (Huo *et al*., 2020).

SCL is vital for SAG because agile supply chains have to be ready to respond to market shifts and turbulences (Gölgeci & Gligor, 2022). Conceptually, SAG depends on the organization's capacity to learn from its actions and the environment and adapt quickly. Research indicates that SCL can greatly enhance SAG (Tse *et al*., 2016), though further research is needed. Firms with better SCL can quickly change their strategies and operations and thus enhance the firm's agility to react to market conditions and shocks in the short term (Zhu *et al*., 2018).

This relationship can also be explained using OIPT, which suggests that information processing requirements should be aligned with information processing capabilities (Tushman & Nadler, 1978) to cope with uncertainties. SCL achieves this alignment by obtaining, analyzing, and sharing information to reduce risk and improve decision-making (Azadegan *et al*., 2019). SAG fits this alignment between the OIP requirements and capabilities to respond quickly and efficiently to changes and events.

H1: *Supply Chain Learning has a positive significant effect on Supply Chain Agility*

Supply Chain Adaptability as a Mediator

SCAD deals with the ability of the supply chain to transform its functionality and its strategic tactics in response to shifts in the long-term trends of the macro environment (Feizabadi & Alibakhshi, 2022). SCAD enables the supply chain to remain effective and efficient in highly volatile markets (Bhatti *et al*., 2024) which presents a variety of disruptions and opportunities.

While scholars have studied SCAD, SAG, and SCL together, , the research lacks answers to the relationship among the three concepts. Like for example, the prior research has discussed the impact of SCAD on SAG (Aslam *et al*., 2018; Wamba *et al*., 2020); however, SCL on SCAD and SCAD as a mediating variable between SCL and SAG has not been studied. Conceptually, SCL enhances firms' ability to decode information across the supply chain network; hence, it helps firms get ready for change by anticipating it (Bessant *et al*., 2003). SCAD tends to alter its supply chain for the long term, ultimately leading the firm to alter for the short term.

OIPT suggests that information processing requirements and the capabilities need to be aligned to handle uncertainty and complexity (Galbraith, 1974). SCL is a source of information processing requirements for enhanced decision-making (Trautmann *et al*., 2009), which leads the SC to possess information processing capabilities like SCAD, which serves supply chains longer during disruptions. If collectively, both informational processing requirements and capabilities fit in efficiently utilizing a capability like SAG, supply chains would become more resilient (Dubey *et al*., 2022).

Therefore, we propose the following

H2: *Supply Chain Adaptability mediates the relationship between Supply Chain Learning and Supply Chain Agility*

BDA Management Capability as a Moderator

Research on BDA has been done broadly, discussing technologies and methods that can enhance SC operations and outcomes. Technological and managerial dimensions of BDA have been explored in studies like Wamba and Akter (2019) who explored the effect of BDA on SAG. In this study, we investigate specifically BDAMC, which covers strategic alignment, coordination, regulation, and promoting the data culture (Karaboga *et al*., 2023). While the overall BDA focuses on technological implementation and talent utilization, BDAMC is a capability known to plan, coordinate, and implement BDA in a company. It focuses on integrating these technologies into business processes to effectively use data to achieve the firm's strategic goals and, ultimately, the mission and vision of the company (Akter *et al*., 2016).

Conceptually and theoretically, SCL, SAG, and SAD are all about utilizing the information at the right time; the more and better the information processing requirements, the better the capability and fit. So, to strengthen this relationship, BDAMC can be considered a strategic advantage within the framework of the OIPT, which helps a company manage a vast amount of data efficiently (Srinivasan & Swink, 2018). OIPT highlights the need for horizontal links and vertical databases to enhance the information processing capability (Galbraith, 1977). So, BDAMC is capable of achieving the strategic fit.

So we hypothesise

H3a: *Big Data Analytics Management Capability moderates the relationship between SC Learning and SC Agility*

H3b: *Big Data Analytics Management Capability moderates the relationship between SC Learning and SC Adaptability*

H3c: *Big Data Analytics Management Capability moderates the mediated relationship between SC Learning and SC Agility through SC Adaptability*

Hypotheses have been depicted as research model in Figure **1** for clear understanding.

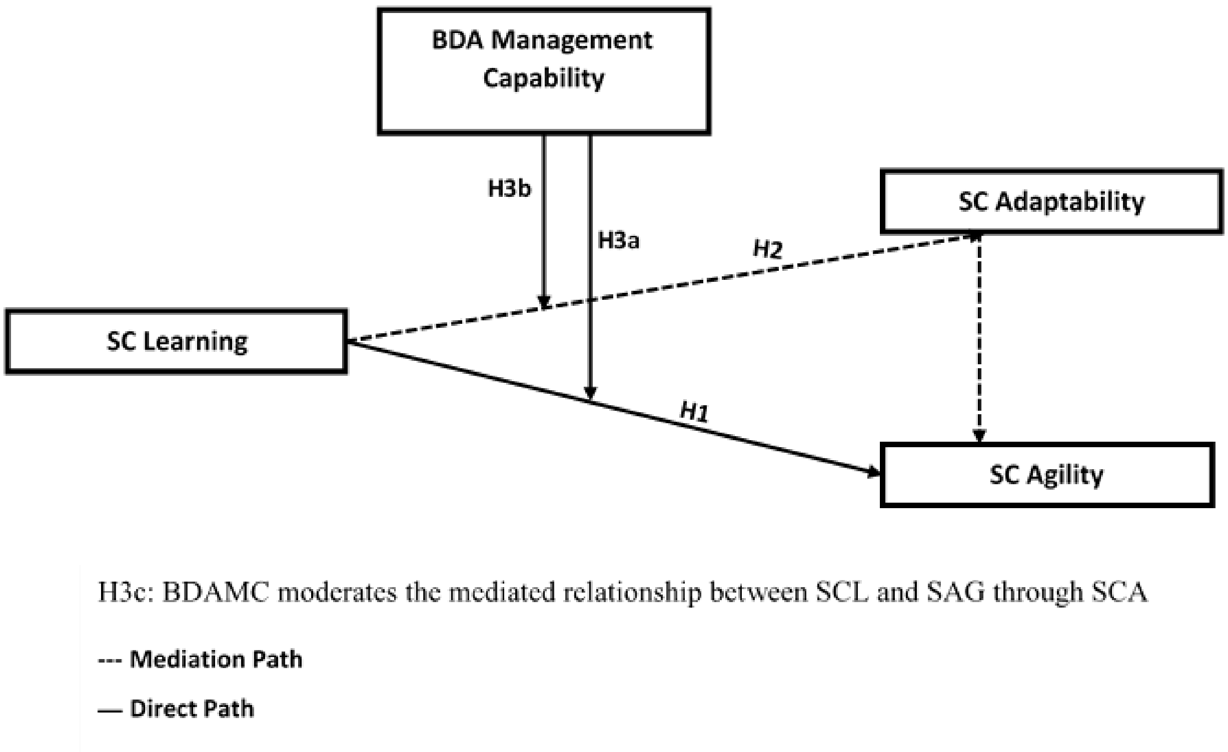

Figure 1. Research Model

3. METHODOLOGY

This research follows the Saunders Research Onion framework (Saunders & Lewis, 2017), which offers a systematic and comprehensive approach to the methodology. The first step entails identifying our philosophical perspective, positivism, which deals with observable and measurable results in an orderly world. This aligns with our choice of a deductive approach in hypothesis testing using empirical data derived from theoretical propositions. The research method employed in this study is a survey, which is useful in providing particular and measurable information from respondents and collecting up-to-date and accurate primary data.

Data Collection

This study is based on large-scale manufacturing firms in Punjab, Pakistan, which have been chosen for their importance in manufacturing activities and their contribution to the economy of the country (SECP, 2020).

The socioeconomic transformation that is occurring at a fast pace in Punjab makes it an ideal place to examine the supply chain in an emerging market (IMF, 2024). To ensure the generalizability of the findings, we employed a stratified sampling method to select a cross-section of manufacturing organizations. This was important in ensuring that the samples within each stratum were as similar as possible, thus improving the validity of our survey data (Singh & Masuku, 2014). The strata were based on the sector's contribution to GDP.

As the operations of large manufacturing firms are complex and extensive, it is important to examine the effects of BDAMC on supply chain operations within large firms (Mikalef *et al*., 2019). Large firms are defined based on the annual sales turnover specified by the Small and Medium Enterprises Development Authority (SMEDA, n.d) of PKR 800 million and above.

The data was collected through multiple means such as emails, WhatsApp messages, and personal visits, as these are reported to increase response rates in Pakistan (Wadood *et al*., 2022). The overall response rate that we obtained was 21.1%, which is in line with other research conducted in the area (Saleem *et al*., 2023). To minimize the threats to the common biased method in our study, we employed a multi-respondent survey design where different sections of the survey were given to different supply chain professionals in the same company, as suggested by Podsakoff *et al*. (2012). The sample selected for our study is spread across various sectors, and this is because Pakistan's manufacturing sector is diverse in terms of its economic contributions. The textile industry is the most dominant, with a 21% contribution to GDP and 24% of the respondents. Other key sectors include food (16% employment share with 13% GDP contribution), chemicals (8% each in terms of GDP and employment), and textiles (7% with 16% employment). The least dominant sectors are fabricated metal, machinery and equipment, and other manufacturing industries with low GDP contributions and sample sizes.

Our sample has a good representation in terms of company age and size. Those between 1 and 3 years old and 4 to 9 years old account for 31 percent, respectively. Only 3% of the sample was between 0 and 5 years of age, and those 10 years and above were 37%. 5%. Regarding the number of employees, 48. 7% of the companies have between 101 and 500 employees, and 51.3% have more than 500 employees. The respondents' profiles indicate they have diverse experience in the supply chain management field. The largest group is those with more than 15 years of experience at 42%, then those with 10 to 15 years at 36.6% with 11 to 15 years of experience. Those with 6 to 10 years and 1 to 5 years of experience constitute 17 percent of the respondents. 9% and 3.6%, respectively. Furthermore, 31.7% of respondents have been with their current company for 1 to 3 years, 27. 2% for less than a year, and 41% for 4 years or more.

Measures

This research measured the SCL, BDAMC, SCAD, and SAG using existing scales for validity and reliability. SCL was measured by the levels of continuous improvement and information sharing using a scale by Flint *et al*. (2008). BDAMC was assessed in terms of the strategic application and modification of big data analytics based on the scale by Akter *et al*. (2016). SAG was assessed by the scale developed by Chakravarty *et al*. (2013). Firms' SCAD was measured based on the firm's ability to respond to changes in the market promptly and was adopted from Schoenherr and Swink (2015). All scales in this study were measured using a 1 to 5 scale. Specifically, BDAMC and SCA were measured using a "Never" to "Always" scale, SCL was measured using a "Not a priority" to "Very high priority" scale, and SAG was measured using a "Strongly disagree" to "Strongly agree" scale.

4. RESULTS

The analysis section of this study includes descriptive statistics, reliability and validity tests, model fitness assessment, and structural model analysis. The analysis is done using SPSS and AMOS Ver.24.

Measurement Model Validation

Confirmatory Factor Analysis (CFA) was conducted to scrutinize the constructs' reliability and validity to ensure our measurement model's robustness and validity. Each item's loading on its respective construct was required to surpass the 0.60 threshold, as recommended by Hair *et al*. (2009) for establishing reliability. The analysis indicated that a few items did not meet this criterion, leading to their exclusion to refine the measurement model's accuracy. Items deleted due to low factor loadings include SAG1, SAG6, SCAD3, BDAMC3, BDAMC6, BDAMC14, and BDAMC15.

Composite reliability (CR) scores exceeding 0.70 and Average Variance Extracted (AVE) values above 0.50 demonstrate convergent validity (Hair *et al*., 2009). Discriminant validity is established when the maximum shared variance (MSV) is less than the AVE, and the square root of AVE exceeds inter-construct correlations (Hair *et al*., 2009). Our constructs satisfied these conditions, with CR and AVE metrics exceeding their respective cutoffs, affirming convergent and discriminant validity. Another test used to assess discriminant validity is the HTMT (Heterotrait-Monotrait) ratio. It verifies that the variables understudy are statistically different if they are theoretically different. The HTMT values for all variables were below the 0.85 threshold, proving they are statistically different (Hu & Bentler, 1999). Model fitness was evaluated against Hu and Bentler (1999) benchmarks, indicating an excellent model fit with CMIN/DF ratios between 1 and 3, CFI values above 0.95, SRMR below 0.08, RMSEA below 0.06, and P Close above 0.05. All these psychometric properties can be observed in Table **1**.

Table 1. Measurement Model Validation: Reliability and Convergent Validity.

Indicator (CR, AVE)	**Standardized Loading**
Supply Chain Learning (CR = 0.921, AVE = 0.662)	
SCL1	0.83
SCL2	0.75
SCL3	0.85
SCL4	0.83
SCL5	0.75
SCL6	0.84
BDA Management Capability (CR = 0.950, AVE = 0.597)	
BDAMC1	0.77
BDAMC2	0.90
BDAMC4	0.85
BDAMC5	0.78
BDAMC7	0.82
BDAMC8	0.76
BDAMC9	0.79
BDAMC10	0.71
BDAMC11	0.76
BDAMC12	0.82
BDAMC13	0.68
BDAMC16	0.68
BDAMC17	0.64
Supply Chain Adaptability (CR = 0.807, AVE=0.584)	
SCAD1	0.85
SCAD2	0.74
SCAD4	0.68
Supply Chain Agility (CR = 0.835, AVE = 0.504)	
SAG2	0.75
SAG3	0.63
SAG4	0.69
SAG5	0.72
SAG7	0.73

Note: Items Deleted due to low factor loadings: SAG1, SAG6, SCAD3, BDAMC3, BDAMC6, BDAMC14, BDAMC15

Table **2**, presents the means, standard deviations, and correlation coefficients for the variables under study. It reveals that the mean, the average score for SCAD is mid-range with the highest dispersion among the variables understudy. While that of SAG and BDAMC is less dispersed but represents average mid-range scores. The results also show that SCAD has a positive and significant correlation with SAG, BDAMC, and SCL, suggesting that they are closely linked., BDAMC also displays an overall positive correlation with both SCAD and SAG, while demonstrating a prominent positive relationship with SCAD in particular, this being a significant indicator of its contributions in the area of adaptability and agility. Nevertheless, the correlation between SCL and SAG is rather low and insignificant, so it may be stated that learning in the supply chain does not affect agility. The AVE values on the diagonal support the discriminant validity of the construct when the square root of these values is compared.

Table 2. Correlation, Means, and Standard Deviations.

	Mean	SD	SCAD	SAG	BDAMC	SCL
SCAD	3.116	1.371	0.764			
SAG	2.9	1.173	0.230**	0.71		
BDAMC	2.991	1.006	0.683***	0.302***	0.773	
SCL	3.141	1.055	0.336***	0.12	0.188*	0.813

Note: ***Correlation is significant at 0.001; ** Correlation is significant at 0.01; * Correlation is significant at 0.05; Square root of AVEs are provided on the diagonal

Structural Model

In evaluating our structural model, we first addressed multicollinearity, following Graham (2003) guidance. The analysis using SPSS involved dividing the model into sub-models for validation. The VIF for both models was found to be less than 5, with tolerance values significantly above the 0.2 benchmark (Hair *et al*., 2009), confirming the absence of multicollinearity. To test common method bias, a common latent factor (CLF) was added to the CFA model to capture the common variance among all observed variables in the model. The standardized regression weights of both the models (with CLF and without CLF) were compared, and the difference between both was less than 0.20, proving that CMB is not a problem (Serrano Archimi *et al*., 2018).

The direct effect of SCL on SAG was significant, with a Beta value of 0.292 ($p < 0.001$) as shown in Table **3**. This result supports the hypothesis (H1) that SCL positively influences SAG, indicating that organizations prioritizing learning within their supply chains are better equipped to respond rapidly to market changes and disruptions.

Table 3. Direct Effects.

Path	β	P value
Supply Chain Learning -> Supply Chain Agility	0.292	0.001

It can be inferred from the results of Table **4** that the indirect effect of SCL on SAG through SCAD was also significantly supported (H2). The unstandardized estimate was 0.102, with a lower bound of 0.057, an upper bound of 0.166, and a p-value of 0.001, resulting in a standardized estimate of 0.096 ($p < 0.001$). This finding underscores the significant mediating role of SCAD in the relationship between SCL and SAG, highlighting that adaptability is a crucial mechanism through which learning translates into agility within supply chains.

Table 4. Indirect Effects.

Indirect Path	Unstandardized Estimate	Lower	Upper	P-Value
SCL -> SCAD -> SAG	0.102	0.057	0.166	0.001

The moderating effects analysis presented in Table **5** revealed mixed outcomes. While the interaction between SCL and BDAMC did not significantly moderate the SCL and SCAD (estimate = -0.087, p = 0.122), it significantly moderated the relationship between SCL and SAG (estimate = 0.211, p = 0.002). These results suggest that while BDAMC enhances the impact of SCL on agility, its influence on the adaptability derived from SCL is less pronounced.

Table 5. Moderating Effects.

Moderating Path	Unstandardised Estimate	P-Value
BDAMC_x_SCL -> SCAD	-0.087	0.122
BDAMC_x_SCL -> SAG	0.211	0.002

The moderated mediation analysis, conducted using Hayes' PROCESS Model 8, sought to determine whether BDAMC moderates the indirect effect of SCL on SAG through SCAD. The analysis results provide nuanced insights into the dynamics of these relationships.

With SCAD as the outcome variable, the interaction between SCL and BDAMC was insignificant ($\beta = -0.089$, $p = 0.125$), suggesting that BDAMC does not significantly moderate the direct link between SCL and SCAD. This means that the ability to handle BDAMC does not strengthen or weaken the relationship between SCL and SCAD. On the other hand, the model with SAG as the outcome variable had a significant interaction term ($\beta = 0.2170$, $p = 0.0025$), meaning that BDAMC significantly moderates the direct relationship between SCL and SAG. This suggests that firms with higher BDAMC are more capable of optimizing their learning processes for increased agility. The conditional indirect effects of SCL on SAG through SCAD at different levels of BDAMC were also explored. The results revealed that the indirect effect was insignificant at the low, medium, and high levels of BDAMC. In particular, the indirect effect was 0.0140 at low levels ($p > 0.05$), 0.0108 at the mean level ($p > 0.05$), and 0.0076 ($p > 0.05$) at high levels. So, there was no significant difference between the two groups. The results of this study indicate that the moderation of BDAMC on the SCL to SAG via the SCAD pathway is relatively low. Furthermore, the index of moderated mediation was -0.2. BootSE was 0.0082, and the 95% bootstrap confidence interval was [-0.0213, 0. 0134], which means that the moderated mediation effect was not statistically significant. Hence, BDAMC does not affect the indirect relationship between SCL and SAG through SCAD.

5. DISCUSSION AND CONCLUSION

This study adds value to the literature by testing how SCAD mediates the relationship between SCL and SAG. It also explores the role of BDAMC as a moderator in the relationship between SCL and SCAD and SCL and SAG.. The studied framework sets a clear path for managing disruptions and the acceptance of most proposed hypotheses supports the importance of these variables in improving operational resilience and strategic responsiveness, thereby expanding the literature, including studies like Dubey *et al*. (2023); Wamba and Akter (2019). The study nuances an unexplored importance of SCL in developing SAG. SCL, capturing the information processing needs in our model, provides firms with insight and tools to identify changes in the market, create new ways of operation, and execute strategies efficiently and effectively. This helps organizations adapt more efficiently to potential threats and seize potential opportunities that arise; this adds value to the work of scholars like Gölgeci and Gligor (2022). Similarly, the previously unexplored indirect impact of SCL on SAG via SCAD provides essential findings for improving agility in supply chains. SCAD changes the supply chain strategies predictively through the information received from SCL. The prominence of the SCAD as a mediator highlights that flexibility is crucial to transforming learning into agility, underlining the importance of flexibility for utilizing information and knowledge acquired from the learning processes, and adding value to the work of scholars like Christopher and Holweg (2011).

In addition, BDAMC significantly moderates the relationship between SCL and SAG. BDAMC represents the information processing aspects in our model, which includes strategic alignment, coordination, decision-making, and encouraging data usage (Srinivasan & Swink, 2018). It allows organizations to analyze large amounts of data, gain valuable insights, and act on them quickly, thus boosting the agility derived from learning by allowing faster reactions to market changes and disturbances.

However, BDAMC does not significantly affect the relationship between SCL and SCAD, indicating that while BDAMC enhances the direct impact of learning on agility, it has a limited impact on adaptability. Strategic planning and flexibility depend more on the SCL's consistent understanding and the ongoing improvement that stems from it. The results of the moderated mediation analysis show that BDAMC plays a significant role in moderating the direct relation between SCL and SAG but does not significantly impact the indirect effect of SCL on SAG through SCAD. This distinction implies that BDAMC is more important in the initial agile action supported by learning than the long-term strategic change that SCAD supports. Firms should direct their BDAMC strategy towards improving agility; however, it is important to note that benefits for adaptability may require different approaches (Wamba & Akter, 2019).

Theoretical Implication

Our findings contribute to the OIPT by illustrating how information processing capabilities, particularly through BDAMC, can transform SCL into strategic outcomes such as SAG and SCAD, extending the research work of Saha and Rathore (2024) and Lu *et al*. (2024). This study enriches the theoretical discourse by demonstrating how BDAMC and SCL, as sources of information processing requirements, facilitate information processing capability (SAG) and how a fit between information processing requirements and capability is made effective using SCAD.

Managerial Implication

The findings of this study are significant for practitioners in many ways. First, it highlights the need to enhance the analytics capacities by improving BDAMC for strategic big data management. The authors suggest that managers should make BDAMC a central competency for organizations to take full advantage of big data, especially in improving the supply chain's flexibility and responsiveness. Also, the findings show that a learning culture should be nurtured so that the supply chain culture can capitalize on BDAMC. Thus, firms that are more focused on the processes of learning and data-driven decision-making will be able to predict disruptions and act more quickly and effectively.

Limitations and Future Research

Nevertheless, this research has some limitations. This research is based on manufacturing firms in Punjab only, and the supply chain dynamics may vary from region to region. This study was conducted in cross-sectional settings and used self-report measures; therefore, future research could include more quantitative data or follow-up data to confirm and elaborate on the presented results. SCL is limited to information within the supply chains, while customer needs and wants are continuously changing, So future research can focus on variables that extract information beyond the supply chain, like market orientation, and to cope with customer needs and wants, variables like innovativeness can be utilized.

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