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Enhancing Supply Chain Performance and Agility in the Healthcare Industry Through Big Data Analytics: A Complex Adaptive Systems Theory Approach

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Abstract

In the absence of robust data integration and analytics framework, healthcare facilities are faced with the difficulty of aligning inventory with demand accurately. This paper investigated the role of BDA capacity in enhancing supply chain performance (SCP) in the health industry of Ghana through supply chain agility (SCA) in the midst of supply chain complexity (SCC). The cross-sectional study therefore surveyed 288 heads of the supply chain and logistic departments of health facilities in the Ashanti Region of Ghana. The data was preliminary analyzed using IBM SPSS 25. Reflective constructs were validated through confirmatory factor analysis (CFA) using LISREL 8.50. The hypotheses were tested using Hayes PROCESS model 14. The findings show that BDA capability and SCA both positively impact SCP, with SCA partially mediating this relationship. SCC does not significantly moderate the indirect effect of BDA capability on SCP through SCA. Overall, BDA capability improves SCP both directly and indirectly through SCA, and while SCC has a direct effect on SCP, it does not significantly alter the mediation pathway. In conclusion, BDA capability enhances SCP directly and through SCA, reinforcing agility's critical role. While SCC impacts SCP directly, it does not strengthen the BDA–SCA–SCP pathway, highlighting the need for strategic collaboration efforts. Managerially, enhancing BDA capabilities significantly improves SCP, both directly and through SCA, making agility essential for data-driven performance gains. While SCC impacts SCP directly, it does not strengthen the BDA–SCA–SCP pathway, requiring strategic collaboration efforts. Investing in analytics and agility helps healthcare organizations navigate industry demands and operational uncertainties effectively.

Keywords: BDA Capability; Supply Chain Performance; Supply Chain Agility; Supply Chain Complexity.

1. Introduction

The dynamic and complex today's healthcare environment is persistently confronting a growing supply chain challenges (Ronen et al., 2018). The sheer volume of data increase impacts overall supply chain performance (SCP) and efficiency (Rosário & Dias, 2023). In the healthcare industry, data is generated continuously from various sources, including patient records, inventory management systems, supplier communications, and regulatory compliance documents (Javaid et al., 2024). With this influx, supply chains often struggle to ensure timely processing, accuracy, and consistency of data, which are essential for effective decision-making (Oriekhoe et al., 2024). The fragmentation of data across numerous platforms and departments can lead to visibility gaps and difficulties in demand forecasting, resulting in stockouts, overstock situations, and delays (Bilal et al., 2024). Additionally, without a robust data integration and analytics framework, healthcare facilities are faced with the difficulty of aligning inventory with demand accurately, impacting service quality and cost (Tadayonrad & Ndiaye, 2023). The persistence of these data-related problems contribute to increased operational costs, inefficiencies in replenishment cycles, and ultimately, patient care disruptions (Balkhi et al., 2022). These supply chain problems are more profound in sub-Saharan Africa

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(SSA) where there is higher disease burden, limited healthcare infrastructure, and shortages of healthcare professionals (Mekonen et al., 2024). However, the level of interest and adoption of Big Data Analytics (BDA) in the healthcare industry in SSA is still low (Kipo-Sunyehzi, 2021), and far behind the high-income countries, where healthcare efficiency and health outcomes are far better. The reliance on the traditional process for managing data in the healthcare industry has become extremely difficult (Awrahman et al., 2022). Consequently, investment in BDA has become vital to SCP in the healthcare system.

The traditional database mechanism is now recognized as insufficient and inadequate in managing the growing complex and massive data in the healthcare industry (Ramesh & Santhi, 2020), due to its inability to handle the volume, variety, and velocity of healthcare data generated daily (Chen et al., 2020). With the rapid expansion of electronic health records, diagnostic images, patient monitoring data, and information from IoT-enabled medical devices, healthcare organizations require more advanced, scalable solutions that traditional databases cannot offer (Parihar et al., 2024). BDA provides a solution by enabling the integration of diverse data sources, real-time processing, and advanced analytical capabilities that allow healthcare organizations to derive meaningful insights and make informed decisions quickly (Khatib et al., 2024). BDA enable healthcare providers to analyze large volumes of unstructured and structured data, supporting predictive modeling and proactive decision-making to improve patient outcomes and streamline operations (Šajnović et al., 2024). Additionally, BDA tools can process real-time data from multiple points within the supply chain to identify potential disruptions, improve inventory control, and minimize waste, which is crucial in reducing costs and ensuring timely access to medical supplies (Pradhan et al., 2021). Moreover, BDA enhances interoperability across healthcare platforms, enabling seamless data sharing and collaboration among different healthcare departments and organizations (Batko & Ślęzak, 2022). This interoperability is essential in achieving a holistic view of patient care, allowing healthcare professionals to make data-driven, patient-centered decisions while reducing redundancies and delays in care (Gopichand et al., 2024). Big Data technologies, such as machine learning and artificial intelligence, also enhance pattern recognition within healthcare data, helping to identify trends and support personalized treatment plans that improve patient outcomes (Alowais et al., 2023).

In the nutshell, BDA transforms the healthcare industry by providing the tools necessary to manage vast data quantities effectively, allowing healthcare facilities to respond dynamically to changes in demand and make more precise, data-driven decisions (Bahrami et al., 2022). This transformation is crucial for enhancing the supply chain agility (SCA) of the healthcare industry, as it enables organizations to quickly adapt to fluctuations in patient needs, inventory levels, and logistical constraints (Hasan et al., 2024). SCA, which is the ability to respond rapidly and efficiently to changing conditions, becomes achievable as BDA supports real-time monitoring, predictive insights, and proactive planning (Bag et al., 2023). With enhanced SCA, healthcare providers can better anticipate demand surges, such as those seen during pandemics or seasonal flu spikes, and adjust procurement and distribution plans accordingly to prevent stockouts or wastage (Bilal et al., 2024). BDA also improves visibility across the entire supply chain by integrating data from various stakeholders, including suppliers, manufacturers, and distribution centers (Khatib et al., 2024). This end-to-end visibility allows healthcare organizations to identify potential bottlenecks, manage risks proactively, and optimize transportation routes and delivery schedules (Olutimehin et al., 2024). By supporting agile responses to both routine and unexpected challenges, BDA helps ensure that essential medical supplies and equipment are always available where they are needed most (Susitha et al., 2024).

Notwithstanding the capacity of BDA to enhance SCA, its implementation in the healthcare supply chain is challenging due to the volume, variety, and velocity of data generated across various stages of the supply chain (Talwar et al., 2021). Furthermore, the healthcare supply chain must address privacy concerns, data interoperability issues, and regulatory compliance, which add layers of complexity to effectively utilizing BDA (Benzidia et al., 2024). To navigate these complexities, the application of Complex Adaptive Systems (CAS) theory offers a valuable framework for understanding healthcare supply chains as interconnected, adaptive networks (Talukder et al., 2024). CAS theory, traditionally applied to systems with multiple interacting components that exhibit nonlinear behaviours, can provide insights into how healthcare supply chains can self-organize and evolve in response to internal and external pressures (Notarnicola et al., 2024). Viewing the healthcare supply chain as a CAS allows for a systems-oriented approach to managing unpredictability and change, emphasizing adaptability, interdependence, and decentralized decision-making (Choi, 2023). By applying CAS principles, healthcare organizations can enhance their supply chains' agility, making them more responsive to unforeseen events and fluctuations in demand while supporting long-term resilience and sustainability (Ahmad et al., 2024). However, many studies in the extant literature, particularly those emphasizing on issues of supply chain in the healthcare industry seemingly oversimplify the relationship between BDA and SCP without taking into consideration the dynamics of SCA and complexity (Singh et al., 2021; Al-Shbail et al., 2022; Bahrami et al., 2022; Galankashi et al., 2024).

The role of SCC in the relationship between BDA capability and SCP is often underexplored. However, the inherent complexity within healthcare supply chains can drive both innovation and resilience (Bahrami et al., 2022). In the context of complex adaptive systems, the interaction of multiple stakeholders, processes, and technologies fosters diverse perspectives and collaborative problem-solving (Syahchari et al., 2022). This environment encourages the co-creation of solutions, where partners bring unique capabilities, expertise, and insights, enabling the development of innovative strategies and approaches that would be difficult to achieve in more linear, simplified systems (Ahmad et al., 2024). Moreover, SCC enhances resilience by facilitating adaptive responses to disruptions (Al-Darras & Tanova, 2022). A complex healthcare supply chain, supported by BDA capabilities, can quickly share information, resources, and alternatives when facing challenges such as supply shortages, regulatory changes, or market fluctuations. The ability to swiftly adapt and collectively solve problems strengthens the overall agility of the supply chain, allowing it to withstand and recover from disruptions more effectively (Oriekhoe et al., 2024). Through BDA, this adaptive capacity is amplified, providing healthcare organizations with the tools to make data-driven decisions that enhance both performance and agility in the face of uncertainty.

This paper therefore explores the synergy between BDA and CAS theory to propose a comprehensive approach for enhancing healthcare SCP and agility. By leveraging BDA within a CAS framework, healthcare organizations can facilitate continuous learning, real-time adaptation, and effective resource utilization, ultimately leading to more robust and efficient supply chain operations. This study contributes to the emerging discourse on digital transformation in healthcare by demonstrating how advanced analytical tools, combined with systems thinking, can drive a shift toward resilient, agile healthcare supply chains that are better equipped to handle the complexities of the modern healthcare landscape. Through this approach, healthcare organizations can optimize their supply chain processes, minimize operational risks, and improve their capacity to deliver high-quality care in a rapidly changing environment.

2. Theoretical Background and Hypotheses Development

Complex Adaptive Systems exist in almost every aspect of life as well as in every realm of research, healthcare systems inclusive (Ahmad et al., 2024). The CAS Theory serves as a powerful lens for understanding how healthcare supply chains can become more agile and efficient through BDA. In a healthcare supply chain, countless interconnected elements—including suppliers, distributors, healthcare providers, and patients—interact and adapt in response to changing conditions. CAS Theory recognizes that such systems are dynamic, meaning they evolve based on the behaviour of individual agents and environmental feedback, making traditional, static models inadequate (Araja, 2022). BDA introduces an additional layer of responsiveness by aggregating, analyzing, and forecasting trends in real-time, which enables each "agent" in the healthcare supply chain to make informed decisions (Ratnapalan & Lang, 2019). This real-time adaptability is vital in healthcare, where supply chain disruptions can directly affect patient outcomes.

CAS Theory also emphasizes decentralization and distributed decision-making, as agents in complex systems respond independently yet collectively, without a single, central authority directing them (Ahmad et al., 2024). BDA aligns with this principle by empowering different parts of the supply chain with actionable insights, rather than requiring centralized control. For instance, hospital administrators can leverage data insights to predict inventory needs, while suppliers use real-time analytics to optimize delivery routes or anticipate demand spikes. In essence, BDA enables each agent to act autonomously yet in harmony with others, ultimately fostering a more agile and responsive supply chain. This is critical in the healthcare industry, where rapid response to fluctuating patient needs, regulatory requirements, or disruptions—such as those seen during pandemics—is essential.

Additionally, CAS Theory highlights the importance of feedback loops and continuous learning, both of which are integral to BDA (Teo et al., 2024). In a healthcare supply chain, data flows continuously between points, allowing for adjustments based on the latest information about stock levels, demand forecasts, or delivery schedules (Ahmad et al., 2024). Through feedback loops facilitated by Big Data, supply chain agents can detect inefficiencies, learn from past patterns, and adjust their strategies accordingly. This iterative learning fosters agility, as the system continuously adapts to new data, becoming more efficient over time. By using BDA within a CAS framework, healthcare organizations can create a resilient, self-optimizing supply chain capable of swiftly responding to challenges and sustaining high performance, even in the face of complexities. This theory therefore provides a strong ground to the framework in Figure 1.

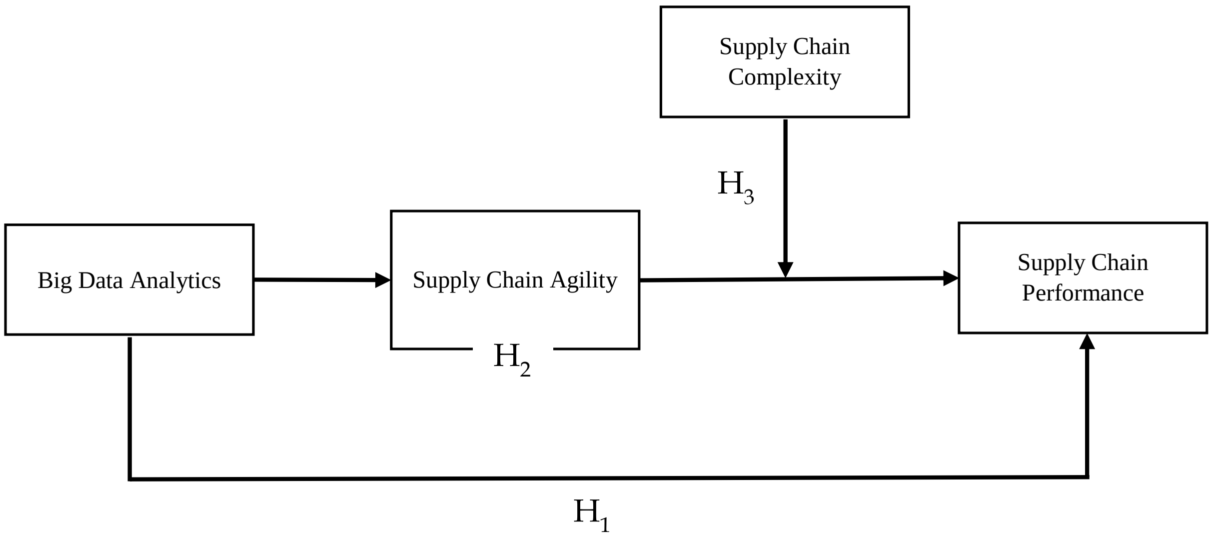

Figure 1. Conceptual Framework of the Study

2.1 Big Data Analytics and Supply Chain Performance

Traditionally, BDA emerged primarily to stimulate higher level of SCP (Jha et al., 2020). This assertion is supported by several studies in the extant literature that have reported significant positive effect of BDA capability on SCP (Singh et al., 2021; Al-Shbail et al., 2022; Bahrami et al., 2022). For instance, the study of Zhang and Li (2022) surveyed Chinese manufacturing firms in Asian economy during COVID-19 and reported that enhanced BDA capacity of SME manufacturing firms stimulates higher level of SCP. A cross-sectional study of Bahrami, Shokouhyar and Seifian (2022) that involved 187 firms showed that BDA capabilities improve SCP even in the face of supply chain complexities. BDAs was reported by Al-Shbail, Maghayreh and Awad (2022) to play significant role in overcoming supply chain disruptions and enhancing SCP sustainability. The usage of sophisticated BDA techniques and methods enhance the BDA capacity of firms, which consequently enhances their decision-making processes and optimizes their supply chain operation efficiency (Hasan et al., 2022; Nodoust, 2024).

BDA capabilities are perceived as an extended organizational resources that can be utilized to create value, and competitive advantage in order to generate sustainable SCP (Mikalef et al., 2019; Wamba S. F. et al., 2020). In the midst of supply chain complexities and uncertainties, BDA capabilities equips business units with the necessary information for effective and efficient decisions in supply chain management to generate higher performances (Wang et al., 2016). With BDAs reported to enhance the flexibility, efficiency and adaptability of firms in the process of SC management decision-making (Corte-Real et al., 2020), this study hypothesizes that:

H_1: BDAs positively and significantly affects SCP

2.2 Mediating Role of Supply Chain Agility

BDA Capability, which includes data processing, predictive analytics, and real-time insights, provides firms with critical information needed to respond quickly and effectively to supply chain disruptions or demand shifts capabilities (Sabahi & Parast, 2020). Previous studies have therefore reported positive and significant linkage between BDA capability and SCA (Dubey et al., 2022; Hammouri et al., 2022; Khalil et al., 2023). The achieved agility is essential for maintaining high SCP, as it allows firms to meet customer expectations, minimize lead times, and optimize resource use (Panigrahi et al., 2022). Previous studies therefore report positive and significant impact of SCA on SCP (Güner et al., 2018; Barhmi, 2022; Çetindaş et al., 2023; Güneş, 2023). By integrating insights from BDA, firms can make swift, data-informed decisions, thus increasing their adaptability and resilience—key aspects of agility. The discussed phenomenon therefore suggests that while BDA Capability offers substantial potential for improving SCP, the full benefits are realized when agility enables a rapid and flexible response to complex supply chain dynamics. This relationship aligns with dynamic capabilities and resource-based theories, which highlight agility as a pivotal mechanism through which data-driven insights translate into enhanced performance. Based on theory and empirical evidence, this paper hypothesizes that:

H_2: SCA mediates the relationship between BDA capabilities and SCP.

2.3 Moderated Mediation Role of Supply Chain Complexity

BDA Capability enhances a firm's ability to process large volumes of data, providing actionable insights that can improve responsiveness, adaptability, and overall SCA (Dubey et al., 2022; Xie et al., 2022; Khalil et al., 2023). This agility is crucial for SCP as it allows firms to quickly respond to market fluctuations and operational disruptions. However, SCCC, characterized by diverse products, processes, and geographies, can either enable or impede the agility gained through BDA (Chand et al., 2022). In highly complex supply chains, the benefits of BDA on agility—and consequently on SCP—may diminish due to challenges in implementing insights across complex networks (Akin-Ateş et al., 2022). Conversely, in simpler supply chains, agility may be more easily achieved and thus effectively mediate BDA's impact on SCP. This dynamic aligns with contingency and complexity theories (Ahmad et al., 2024), suggesting that SCC conditions the effectiveness of agility as a mediator, reinforcing the critical role of contextual factors in achieving optimal performance outcomes. This paper therefore hypothesizes that:

H_3: The mediation role of SCA in the relationship between BDA and SCP is conditioned on the interaction between SCC and SCA.

3. Method

3.1 Design, Population, Sample Size and Sampling Method

With the primary purpose of explaining the causal relationship between BDA capabilities and SCP through SCA, in the face of supply chain complexities, the explanatory research design is deemed appropriate research design. It is also described as cross-sectional, since it covered single time period. The target population were all heads of the supply chain and logistics departments of all the 530 health facilities in the Ashanti Region of Ghana. Out of the total 530 health facilities in the Ashanti Region, 170 are under the operation of Ghana Health Service (GHS), 71 are operated by the Missions, 281 are operated by private institutions, and 8 operated by the Ashanti quasi-government. The minimum efficient sample size of 228 calculated through the Yamane Taro formula (Yamane, 1967), considering a target population of 530 and margin of error or precision of 0.05 or 5%.

With the 530 health facilities operated and managed by four different units, it was essential to limit any influence of such heterogeneity on the research. The researcher therefore employed the Krecjie and Morgan formula to calculate sub-sample size of sub-groups (Krejcie & Morgan, 1970), in order to ensure the inclusion of sampling units from all groups within the population, using the proportion formula in the form of s=XS/P. Thus, the considerations were sub-populations (X), total sample size (S) and total population of the study (P). Based on the calculation, the distribution of the sample size by administration units was 73 Ghana Health Service, 31 Missions, 121 Private Institutions, and 3 Ashanti Quasi-Government.

A multistage sampling method was employed in the sampling of the supply chain management logistics heads of the health facilities. This technique was employed since the sampling units were heterogeneous on the basis of clusters of health facilities under different administrative or operational units. Thus, the health facilities in the Ashanti Region could be structured into four strata, including Ghana Health Service, Missions, Private Institutions and Ashanti Quasi-Government. Thus, in the first stage of the sampling process, the sampling units were stratified into four strata on the basis of administrative units through stratified sampling method, in order to ensure the inclusion of sample units from all administrative units. In the second stage, the allotted sub-sample sizes of the units were sampled through simple random sampling by balloting procedure, since units within the same administrative units were deemed homogeneous. In the balloting process, sample units within an administrative body were represented by names written on pieces of paper, folded and shuffled in a bowl, and the required units randomly selected without replacement.

3.2 Data Collection Method

Primary data was collected through a structured questionnaire that focused on BDA capability, SCA, SCC, and SCP. The questionnaire was administered using both face-to face and online approaches in order to increase the response rate. The supply chain management and logistics heads of the sampled 73 health facilities under the administration of the Ghana Health Service were surveyed through face-to face method. A called was placed to the heads, and dates scheduled for the survey process. All individuals that declined their participation were replaced with heads of new health facilities. However, the 121 heads of the supply chain and logistics units of the health facilities under the operation of private institutions were surveyed through online approach by seeking authorisation, gathering emails and phone numbers of the supply chain management and logistics heads of the facilities, and subsequently, sending them google form survey links. The heads of the supply chain management and logistics units of the 31 missionary health facilities and the 3 health facilities under the operation of the Ashanti Quasi-Government were also surveyed through face-to face method. In totality, 228 questionnaires were fully administered.

3.3 Constructs Development

Four main constructs were measured. BDA capability was measured using the 20 validated measurement items of Al-Darras and Tanova (2022). The sub-constructs measured under BDA capability were data-driven culture, organisational learning, technical skills, BDA infrastructure, and BDA management skills. Each of these sub-constructs were measured using 4-items. The moderating variable, supply chain complexity (SCC) was measured using 12-items adapted from Bozarth, Warsing, Flynn, and Flynn (2009). The sub-constructs of SCC measured were downstream complexities, internal complexities and upstream complexities. The 4-items employed in the measurement of the upstream complexities are accredited to Bozarth and Edwards (1997), da Silveira (2005), and Vollmann et al. (2005). The 3-items for measuring internal complexity were adapted from Thonemann and Bradley (2002), Huang et al. (2005) and Closs et al. (2008). The 6-items for measuring upstream complexity were adapted from Choi et al. (2001), Wu and Choi (2005), and Goffin et al. (2006). The mediating construct, SCA was measured using the validated 9-item scale of Gligor, Esmark, and Holcomb (2015). The dependent variable, SCP was measured using the 11-items scale of Gunasekaran et al. (2017). All items were measured on a 7-point agreement Likert-scale (strongly disagree = 1 to strongly agree = 7).

3.4 Data Analysis

Data in Microsoft Excel was edited for inconsistencies and errors, and imported to IBM SPSS Statistics 25. Data in SPSS was imported in free format to LISREL 8.50 for confirmatory factor analysis (CFA). The CFA process involved the validation of the reflective constructs. Discriminant validity was tested through Fornell-Lacker criterion and heterotrait-monotrait ratio of correlations (HTMT). The confirmed observed items were transformed into latent constructs, and the developed hypotheses tested through Hayes PROCESS analysis.

4. Results

4.1 Measurement Model Analysis

The reflective latent variables were measured through CFA using LISREL 8.50 and maximum likelihood estimation method. The reflective scales were initially measured through the conventional approach of beginning the process in sub-sets in order to limit the risk of violating the minimum sample size to parameter ratio (Hair J. F. et al., 2022). Thus, the sub-scales of BDAs, such as BDA infrastructure, data-driven culture, technical skills, organizational learning, and managerial skills were measured together. The sub-scales of SCC, in the form of downstream, upstream, and internal were also measured together. These sub-scales were measured together because they are conceptually related. These separate models were consequently measured together with SCA and SCP in as the final model in Figure 2. In the measurement process, 27 problematic items were deleted and 25 items retained in the final model. All the retained items, their loadings, and their associated t-values are presented in Table 1. Additionally, the Cronbach alpha (CA), average variance extracted (AVE) and composite reliability (CR) of the measured reflective latent variables presented in Table 1. Convergent validity is achieved since all factor loadings were positive and statistically significant. More so, the minimum threshold of 0.5 was exceeded by all the AVE of the latent variables, which also suggests convergent validity, indicating that the reflective constructs explained a large portion of the variance (Hair J. F. et al., 2022). There was also satisfactory and adequate internal consistency of the measurement items of the latent variables, since their CR and CA were all above the threshold of 0.7 (Trizano-Hermosilla & Alvarado, 2016).

Table 1. Validity and Reliability Results

	Measurement Items	Loadings (t-values)
	BDAs (CR=.969, AVE=.794, CA=.901)	
DCult	Data-Driven culture	0.94(Fixed)
OLearn	Organizational Learning	0.89(11.67)
TSkills	Technical Skills	0.92(13.95)
MSkills	Management Skills	0.92(14.67)
Infras	BDA Infrastructure	0.78(10.28)
	Supply Chain Complexity (CR=.940, AVE=.841, CA=.771)	
Down	Downstream complexity	0.98(Fixed)
Intern	Internal complexity	0.74(9.12)
Upstre	Upstream complexity	0.99(9.86)
	SCA (CR=.817, AVE=.692, CA=.805)	
SCA3	The facility can detect environmental risks promptly.	0.75(Fixed)
SCA6	Facility respond quickly to environmental changes by making decisions.	0.90(11.16)
	SCP (CR=.828, AVE=.616, CA=.826)	
SCP5	The primary supply chain can provide ultimate customers with items that are flawless	0.73(Fixed)
SCP8	The primary supply chain can prevent end consumers from receiving items that are incomplete, damaged, or delivered late	0.80(10.47)
SCP9	Being able to reduce channel safety stock at every stage of the supply chain	0.82(10.63)

Chi2	***Df***	***Chi2/df***	***RMSEA***	***NNFI***	***CFI***	***IFI***	***SRMR***
472.22	261	1.809	0.063	0.92	0.93	0.93	0.062

NB: Non-Normed Fit Index (NNFI), Root Mean Square Error of Approximation (RMSEA), Comparative Fit Index (CFI), Standardized Root Mean Square Residual (SRMR)Incremental Fit Index (IFI).

The other heuristics or fit indices in Table 1 were within the acceptable threshold. The RMSEA and the SRMR of all the reflective sub-scales in Table 2 were also all below the required threshold of 0.07, indicating good-fit models. Furthermore, the NNFI, CFI, IFI and the GFI of all the measured sub-scales were above the threshold of 0.90, indicating good-fit reflective latent models.

Table 2. Good-fit Indices

Construct	Chi2	df	Chi2/df	RMSEA	NNFI	CFI	IFI	GFI	SRMR
BDA	76.16	55	1.385	0.043	0.98	0.98	0.98	0.95	0.030
SCA	3.47	2	1.735	0.060	0.99	1.00	1.00	0.99	0.017
SCC	30.46	24	1.269	0.036	0.98	0.99	0.99	0.97	0.034
SCP	8.76	9	0.973	0.000	1.00	1.00	1.00	0.99	0.021

NB: BDAs (BDA), SCA (SCA), Supply Chain Complexity (SCC), SCP (SCP), Goodness of Fit Index (GFI), Root Mean Square Error of Approximation (RMSEA), Non-Normed Fit Index (NNFI), Comparative Fit Index (CFI), Incremental Fit Index (IFI), Standardized Root Mean Square Residual (SRMR)

Figure 2 is Structural Equation Modeling (SEM) path diagram emphasizing on the final validated structure of the reflective constructs utilized in complex model of the study. The SEM structure illustrates the validated reflective model of the dimensions of BDA capability, SCC, SCA and SCP, prior to the unit analysis. Figure 2 is therefore a graphical representation of the results of the final measurement model presented in Table 1. The good-fit indices suggest that the data significantly fit the complex model. Notwithstanding the statistical significance (P<.01) of the normed Chi-square value of the final reflective model of Figure 1, the chi2/df (Chi2/df = 472.22/261 = 1.809) was good, indicating good-fit of the data, since the required threshold of 2 or less was met.

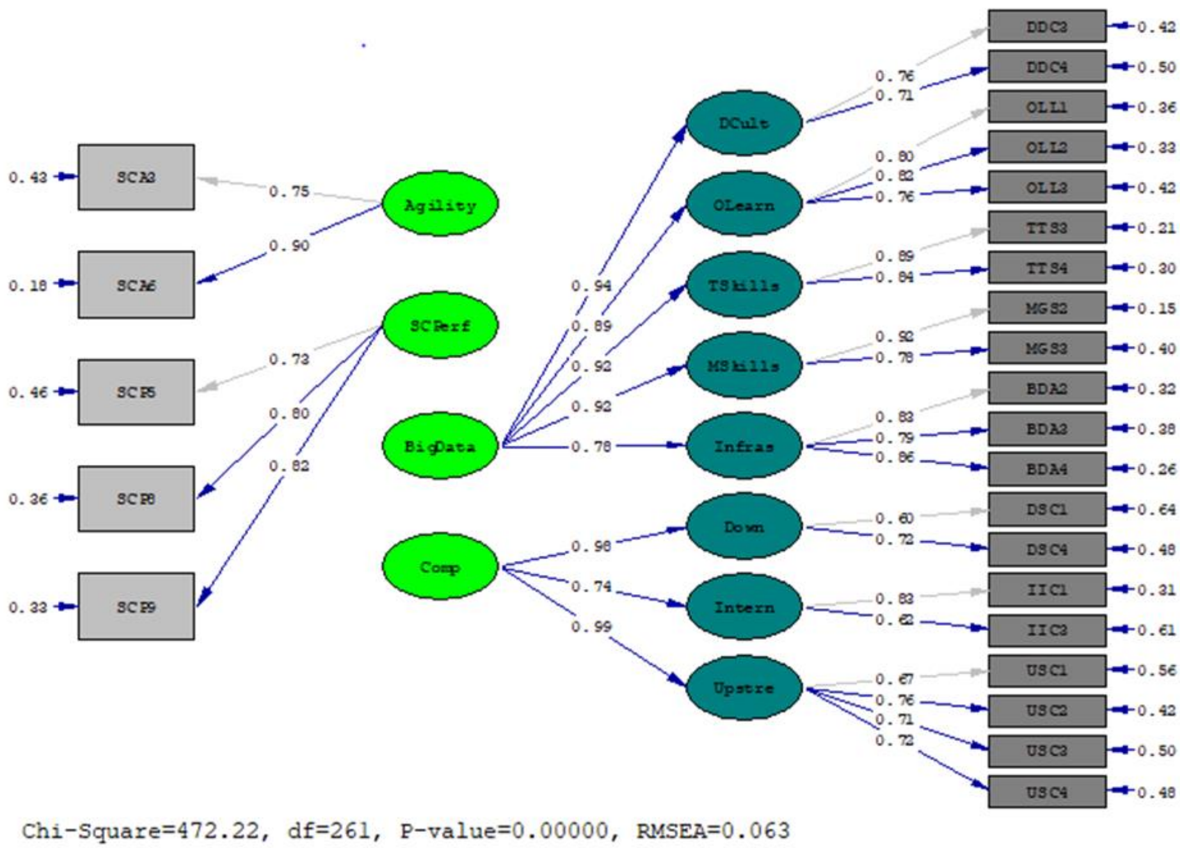

Figure 2. Structure of the Final CFA model

4.1.1 Discriminant Validity

Discriminant validity was ascertained through both the Fornell-Larcker and the HTMT criteria. Based on the results of Table 3, discriminant validity was established through the Fornell-Larcker criterion. The squared-root values of the AVE of the reflective latent constructs shown by the bolded values in the diagonal are all greater than their corresponding off-diagonal inter-construct correlations in the rows and columns, indicating the establishment of discriminant validity (Radomir & Moisescu, 2019).

Table 3. Fornell-Larcker Results

	Constructs	AVE	1	2	3	4
1	BDAs	.794	**0.891**			
2	SC Agility	.692	.673**	**0.832**		
3	SC Complexity	.841	.551**	.416**	**0.917**	
4	SC Performance	.616	.538**	.484**	.593**	**0.785**

However, in the assessment of discriminant validity, the HTMT ratio is often considered superior to the Fornell-Larcker criterion. HTMT has been shown to be more sensitive than the Fornell-Larcker criterion in identifying discriminant validity problems (Hair J. F. et al., 2022). The Fornell-Larcker criterion sometimes fails to detect issues, especially in models with similar constructs or high correlations between constructs, while HTMT is better at identifying when constructs overlap excessively (Radomir & Moisescu, 2019). Based on the questionability of the Fornell-Larcker criterion, this paper further tested discriminant validity using the HTMT. High HTMT values are deemed as indication of the presence of discriminant validity problems (Hair J. F. et al., 2021). For conceptually similar constructs of structural models, Henseler et al. (2015) recommend a threshold of 0.90. However, for more distinct conceptual constructs, Henseler et al. (2015) recommended a more conservative and lower threshold of 0.85. In the context of this paper, the constructs are more distinct, and hence, the threshold of 0.85 was utilized as the basis of conclusion. Table 4 shows that all the HTMT values were below the threshold of 0.85, indicating the meeting of discriminant validity by the reflective latent constructs.

Table 4. HTMT Results

	Constructs	1	2	3	4
1	BDAs	-			
2	SC Agility	0.789	-		
3	SC Complexity	0.671	0.545	-	
4	SC Performance	0.621	0.594	0.743	-

Note: HTMT values are required to be less than 0.85, in the case of distinct reflective latent concepts.

4.2 Correlational Analysis

Descriptive statistics and Pearson's correlational results are presented in Table 5. The established BDAs positively and significantly correlates with SCA (r=.673, P<.01) and SCP (r=.538, P<.01) of the healthcare facilities, suggesting that any significant improvement in the BDAs of the healthcare facilities is associated with improvement in SCA and SCP. The SCA of the healthcare facilities positively and significantly correlates with the SCP (r=.484, P<.01), also suggesting that any significant improvement SCA facilitates corresponding improvement in the SCP. Similarly, the complexity of the SC of the healthcare facilities positively and significantly correlates with SCP (r=.593, P<.01), suggesting that increasing complexity of SC motivated health facilities to institute the right technological capabilities to stimulate higher level of SCP.

Table 5. Descriptive and Inter-Construct Correlation

	Constructs	1	2	3	4	Mean	Std. Dev
1	BDAs	1				5.6	.9
2	SC Agility	.673**	1			5.6	1.1
3	SC Complexity	.551**	.416**	1		5.4	1.0
4	SC Performance	.538**	.484**	.593**	1	5.5	1.1

**. Correlation is significant at the 0.01 level (2-tailed). Scale: [1=Strongly Disagree, 2=Disagree, 3=Moderately Disagree, 4=Neither Agree or Disagree, 5=Moderately Agree, 6=Agree, 7=Strongly Agree]

4.3 Hayes PROCESS Analysis

The Hayes PROCESS Model 14, a moderated mediation model is tested in this part of the paper in order to analyze whether the indirect effect of BDA on SCP through SCA depends on the level of SC complexity. Table 6 as the first part of the model tested the effect of BDA on SCA. Table 6 suggest that BDA explained about 27.95% of the variance in SCA, as indicated by R^2 of 0.2795. BDA has positive and significant influence on SCA (β=.5573, P<.01), indicating that any significant unit change in BDA is associated with about 55.7% increase in the SCA of the health facilities.

Table 6. Relationship between BDA and Supply Chain Agility

Model	Coeff	se	t	P	LLCI	ULCI
Constant	2.4649	.3560	6.9234	.0000	1.7630	3.1669
Big Data Analytics	.5573	.0626	8.8968	.0000	.4338	.6808
R	.5287					
R^2	.2795					
MSE	.8962					
F-Statistic	79.15(1)***					

Outcome Variable: Supply Chain Agility (SCA)

The second part of the model tested the effect of BDA, SCA, SCC and the interaction of SCA and SCC on SCP. About 35.3% of the variance in SCP was explained by these variables, as indicated by the R^2 of 0.3530. Table 7 shows that BDA has direct effect on SCP (β=.1402, P<.05), indicating that any significant unit improvement BDA directly stimulates about 14% increase in SCP. SCA also had positive and significant influence on SCP (β=.4803, P<.01), indicating that any significant unit improvement in SCA is associated with about 48% increase in SCP. The complexities in the supply chain was also found to stimulate significant and positive increase in SCP (β=.3904, P<.05). However, the interaction factor (SCA x SCC) had no significant effect on SCP (β= -0.0280, p= .3670), indicating that the effect of SCA on SCP was not moderated by SC complexity.

Table 7. Direct Effects

Model	Coeff	se	T	P	LLCI	ULCI
Constant	.8501	.9409	.9035	.3674	-1.0052	2.7054
BDA	.1402	.0697	2.0116	.0456	.0028	.2777
SC Agility (SCA)	.4803	.1670	2.8750	.0045	.1509	.8096
SC Complexity (SCC)	.3904	.1797	2.1726	.0310	.0361	.7447
SCA x SCC	-.0280	.0309	-.9041	.3670	-.0890	.0330
R	.5941					
R^2	.3530					
MSE	.7514					
F-Statistic	27.416(4)***					

Outcome Variable: SC Performance; Test(s) of highest order unconditional interaction(s):(M*W = (R2-chng = .0026, F = .8174, df1 = 1.0000, df2 = 201.0000, p = .3670)), M = Mediator, W = Moderator

To probe the conditional indirect effects, Table 8 shows that the indirect effects of BDA on SCP through SCA vary slightly with levels of SCC. At increasing levels of SC complexity, the effect of BDA on SCP through SCA decreases. Evidently, all the indirect effects are significant, with confidence intervals not including zero, indicating that SCA partially mediates the effect of BDA on SCP across different levels of SCC.

Table 8. Conditional indirect effects of BDA on Supply Chain Performance

SC Complexity	Effect	BootSE	BootLLCI	BootULCI
4.0000	.2053	.0689	.0558	.3270
5.5000	.1819	.0500	.0920	.2898
6.5000	.1663	.0608	.0665	.3032

Indirect Effect: BDA Analytics -> SC Agility -> SC Performance

However, the index of moderated mediation is -0.0156 (95% CI: -0.0603, 0.0724), which includes zero (see Table 9). This indicates no statistically significant moderated mediation, suggesting that SCC does not significantly change the strength of the indirect effect of BDA on SCP through SCA.

Table 9. Index of moderated mediation

	Index	BootSE	BootLLCI	BootULCI
SC Complexity	-.0156	.0328	-.0603	.0724

5. Discussion

Big Data Analytic capability plays a crucial role in enhancing SCP directly. The BDA capabilities of healthcare facilities are recognized to increase SCP, which provides sufficient support for the hypothesis (H_1) that BDAs positively and significantly affects SCP. This finding is also consistent with previous studies have reported significant positive effect of BDA capability on SCP (Singh et al., 2021; Al-Shbail et al., 2022; Bahrami et al., 2022). BDA enables improved decision-making through real-time data processing and predictive analytics, allowing supply chains to better forecast demand, optimize inventory levels, and reduce lead times (Santos & Marques, 2022).

However, the effect of BDA capability on SCP was not merely direct, but also recognized to be through SCA. In addition to the impact of BDA capability on agility, SCA itself has a significant and positive effect on SCP, where each improvement in agility is associated with a nearly 48% increase in performance. These findings provide adequate evidence of the partial mediation role of SCA in the BDA capability and SCP linkage, which supports hypothesis H_2. This finding aligns with existing literature that positions agility as a critical enabler of supply chain responsiveness and operational efficiency (Dubey et al., 2022; Hammouri et al., 2022; Zhang & Li, 2022). Strategic investment in analytical capabilities are reported to complement and stimulate higher level of SCA capabilities (Dubey et al., 2019;

Sabahi & Parast, 2020), in the form of production flexibility, risk management resilience, rapid response to changes in demand, advanced data-driven decisions, and collaborative partnerships (Jindal et al., 2021).

Furthermore, while SCC positively impacts SCP directly, the interaction between SCA and SCC does not significantly affect SCP. This suggests that, while complex supply chains may benefit from BDA-driven agility, the agility-performance link is stable and not dependent on the level of complexity. This stability implies that agility remains a valuable asset across various complexity levels, perhaps due to its inherent capacity to address diverse operational demands.

Finally, although SCC slightly reduces the strength of the indirect effect, BDA capability of healthcare facilities continues to indirectly improve SCP via SCA across complexity levels, suggesting that regardless of SCC, the benefits of BDA capability extend beyond agility, providing a consistent positive impact on SCP. Thus, BDA is affirmed as a foundational driver of agility and performance, allowing firms to navigate complexity while maintaining robust supply chain operations. These insights underscore the value of investing in analytics to enhance both direct and mediated performance outcomes within dynamic and complex supply chain contexts.

6. Conclusion

This paper explores the impact of BDA on enhancing SCP in healthcare, with SCA serving as a mediating factor and SCC acting as a potential moderator. It was evident that BDA positively influences both SCA and SCP directly, reinforcing the importance of data-driven approaches in managing healthcare supply chains. Specifically, SCA plays a significant mediating role in translating the benefits of BDA into performance improvements, highlighting agility as a critical component in leveraging BDA's full potential. However, while SCC positively contributes to SCP, it does not significantly moderate the indirect effect of BDA on SCP through SCA, suggesting that increased complexity does not hinder the beneficial impacts of agility within healthcare supply chains.

In essence, the paper underscores the transformative role of BDA in healthcare supply chain management by facilitating agile and responsive supply chains, which are essential for coping with the uncertainties and demands inherent in the healthcare industry. As healthcare supply chains become more complex, the findings suggest that enhancing SCA remains crucial, as it not only improves performance but also sustains the positive impacts of BDA.

7. Implications

In the context of knowledge, this conclusion enhances our understanding of the interplay between BDA capability, SCA, and SCP within healthcare settings, contributing to the existing body of knowledge on supply chain management in complex environments. It reinforces the notion that BDA is not merely a technological tool but a critical capability that drives both direct performance improvements and fosters agility, which is essential for navigating the complexities of modern healthcare supply chains. Furthermore, the finding that SCC does not significantly disrupt the mediation pathway suggests that the benefits of BDA can be realized across various operational contexts, thereby encouraging further exploration of how analytics can optimize performance even in highly variable and intricate systems. This insight calls for a shift in perspective among researchers and practitioners, emphasizing the importance of integrating BDA into strategic supply chain frameworks to enhance resilience and efficiency in healthcare operations.

Managerially, healthcare managers in Ghana should prioritize the development of BDA capabilities as a strategic approach to enhance SCP, both directly and by fostering SCA. By leveraging BDA, managers can improve forecasting, optimize inventory levels, and enable quicker responses to changing supply needs, ensuring a stable flow of medical supplies. While SCC independently affects SCP, it does not disrupt the beneficial effects of BDA-driven agility, indicating that investing in data-driven agility is a resilient strategy across varied complexity levels. This approach can enable healthcare facilities to better manage resources, reduce disruptions, and improve patient care outcomes.

In the context of policy, Christian Health Association of Ghana (CHAG), Ghana Health Service (GHS) and the Ministry of Health (MoH) should institute policies focusing on investment in data infrastructure, analytics training for healthcare workers, and the establishment of standards for data management and sharing across the health sector. Since SCC does not significantly alter the mediation pathway, BDA-driven agility can strengthen supply chain resilience regardless of complexity. Such a policy approach can help ensure a steady supply of critical medical resources, reduce response times in crisis situations, and ultimately improve patient care and health outcomes nationwide.

In terms of theory, the findings support the Complex Adaptive Systems Theory by illustrating how BDA capabilities enable healthcare supply chains to behave as adaptive systems, directly and indirectly enhancing SCP through SCA. In line with this theory, BDA empowers healthcare supply chains to process vast amounts of data, allowing them to respond dynamically and adapt to changes in demand or disruptions in real time. The direct effect of SCC on SCP, without significantly altering the mediation pathway, underscores the theory's view that complex systems, such as healthcare supply chains, benefit from both structured data insights (BDA) and flexibility (SCA) to navigate evolving conditions. This adaptability makes the healthcare supply chain more resilient, demonstrating that BDA-driven agility aligns with the principles of Complex Adaptive Systems by enabling responsive and efficient performance even within complex and unpredictable environments.

8. Limitations and Future Research

The focus on healthcare facilities in Ghana may limit the generalizability of the findings to other regions or industries. Differences in healthcare systems, data availability, and cultural factors could influence the relationship between BDA, SCA, and SCP in different contexts. Future research should explore the role of BDA capability, SCA, and SCC in different healthcare systems, particularly by comparing developing and developed countries to assess contextual differences. Ghana's healthcare system, for instance, could be compared to Canada's more developed health system. Additionally, studies could examine other moderating factors, such as regulatory frameworks or digital infrastructure, to better understand their influence on the BDA–SCA–SCP relationship. The cross-sectional design capture data at a single point in time. This design restricts the ability to observe changes over time, making it challenging to determine the long-term effects of BDA on SCP and SCA. Future studies could adopt a longitudinal approach to better understand the long-term impact of BDA on SCP by examining how the relationships between BDA, SCA, and SCP evolve over time.

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