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RESEARCH ARTICLE

Weighing the Capabilities of Big Data Analytics for Sustainable Supply Chain Management in Construction Projects

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Abstract

The construction industry faces significant challenges in implementing sustainable Supply Chain Management (SSCM) practices. This study explores the capability of big data analytics in enhancing SSCM in construction projects. A comprehensive literature review was conducted to identify the benefits, challenges, and barriers of adopting Big Data technologies in SSCM. The findings highlight the importance of big data analytics in improving supply chain visibility, reducing risks, and promoting sustainable practices. The study also identifies several challenges and barriers to the adoption of Big Data technologies in SSCM, including social, economic, and environmental concerns. The research provides insights into the role of big data analytics in driving SSCM in the construction industry. The study's findings have significant implications for construction companies, policymakers, and stakeholders seeking to improve the sustainability of their supply chains. By leveraging big data analytics, construction companies can enhance their SSCM practices, reduce their environmental impact, and improve their bottom line. This study contributes to the growing body of research on Big Data and SSCM in the construction industry.

Keywords Big Data Analytics · Sustainable Supply Chain Management (SSCM) · Big Data · Construction Projects · Supply Chain Sustainability.

1. Introduction

The significance of Supply Chain Management (SCM) is increasingly acknowledged in the construction industry. However, its application has been limited and continues to elicit challenges for both researchers and practitioners (Studer and DeBrito Mello, 2021). Although advancements within the construction sector are gradually gaining recognition (Masood et al., 2022), sustainability remains a common focal point. Analysts examining supply chains (SC) and their management indicate that the effectiveness of local and holistic supply chains could be enhanced by better management of the relationships and interactions among companies (Chandra & Kumar, 2000; Mentzer et al., 2001; Amiri et al., 2021). Sustainable Supply Chain Management (SSCM) involves the effective management of social, economic, and environmental aspects in global construction supply chains. It promotes governance techniques that minimise waste and enhance sustainability while providing economic and societal benefits to all stakeholders throughout the product lifecycle. Implementing SSCM in construction reduces environmental impact, mitigates failure risks, and boosts competitiveness (Suhi et al., 2019). The construction supply chain includes contractors, producers, suppliers,

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builders, engineers, clients, and transporters, all connected through finance, information, and materials. Clients play a key role in shaping the supply chain's structure based on their activities (Goyal et al., 2018).

It is crucial to view the supply chain as a network of interconnected events rather than isolated stages (Carter and Rogers, 2008; Moktadir et al., 2021). A builder can source materials from various suppliers and exchange items with multiple affiliates. SSCM focuses on a broader range of activities for managers, promoting strategies to enhance environmental, economic, and social governance (Goelet al., 2020). Big Data aids in creating digital, value-added supply chains by improving information flow among customers, business partners, and products through automated production (Kagermann et al., 2013; Dallasega, 2018). This integration enhances supply chain performance and transparency (Luthra and Mangla, 2018).

This study explores the capabilities of big data analytics in enabling SSCM in construction projects, identifying the key challenges, potentials, and effective technologies for implementing SSCM, with a focus on Ebonyi State, Nigeria. This research contributes to the existing literature by examining the intersection of big data analytics, Industry 4.0 technologies, and SSCM in the construction industry, providing insights into the Nigerian context. The objectives of this study are to examine the potential of big data analytics in SSCM in construction projects, to identify the effective Industry 4.0 technologies used in SSCM, to assess the challenges in adopting Industry 4.0 technologies in SSCM, and to evaluate the impact of big data analytics on SSCM in construction projects.

2. Literature Review

Studies on SCM have shown that the biggest challenges in adopting SCM technologies are slow IT adoption in material flow management and a lack of motivation from training. Digital technologies play a crucial role in helping companies pursue sustainability initiatives (Amiri *et al.*, 2021; Masood et al., 2022). In light of this, we have developed an overview of digital technologies and their sustainability advantages based on a literature review following the guidelines of Webster and Watson (2002) and vom Brocke et al. (2015). Despite the Capability benefits that advanced technologies offer in enhancing SCM, there remains a lack of comprehensive understanding regarding their effective utilisation and integration into construction projects (Studer et al., 2021; Moktadir et al., 2021). Moreover, limited research has focused on the specific impacts of Big Data technology adoption on supply chain performance within the global construction sector. This knowledge gap prevents the industry from fully leveraging technological capabilities to mitigate cost overruns, improve project efficiency, and elevate overall project performance (Kassem et al., 2018; Lu et al., 2019; Teizer et al., 2017; Azhar et al., 2018; Sacks et al., 2018). The management of material and information flows is a critical priority for construction firms aiming to provide value for their clients' investments (Serpell and Heredia, 2012). The various perspectives on the 4.0 revolution in SCM focus on replacing tasks traditionally performed by humans with machines. This challenge of Big Data, which represents the fourth generation of SCM, encourages businesses to step out of their comfort zones and transform their operations to create products and deliver services more effectively (Sutawijaya, 2020). Big Data represents the automation and data exchange processes designed to enhance efficiency through advanced technologies such as artificial intelligence, robotics, and the Internet of Things (IoT). These technologies facilitate the automation of supply, production, and delivery of goods and services with minimal human intervention (Barreto, Amaral, & Pereira, 2017).

Lauren and Jayashankar (2015) define SCM as the effective administration of the supply process from product or service design to consumer disposal. This process includes planning, procurement, product design, and distribution. According to Mensah et al. (2014), SCM ensures efficiency in managing product and service supplies through a network of organisations. The importance of SCM in the construction sector has grown, as evidenced by an increase in research and publications (O'Brien et al., 2009; Meng et al., 2011). In 2010, two academic journals published special issues on this topic, underscoring its relevance (Ellegaard et al., 2010; Segerstedt and Olofsson, 2010). The construction industry not only drives local development and employment but also enhances economic efficiency (Oladinrin et al., 2012). Key supply chain frameworks in construction include Engineer-to-Order, Make-to-Order, Make-to-Stock, and Assemble-to-Order (Dallasega and Rauch, 2017; Dike and Kapogiannis et al., 2014). Historically, local materials like clay, timber, and straw were used in traditional construction methods (Onyegiri and Ugochukwu, 2016). Operational efficiencies in production and technology are critical for success (Ogunbadejo and Zubair, 2022), and the adoption of advanced technology can improve labour productivity (Okungbowa and Abhulimen, 2021).

Table 1. Summary of some general problems that exist within the construction SCM (***Source:*** *Akintoye et al. (2000), authors' own summary*)

Interfaces	Problem Description
Feed and Engineering Interface	Inaccurate certification, Design alteration, Wrong calculations, prolonged time for design revision and approval
Client Feed	Extended time for Design Changes and approval, No constructability
Engineering Procurement, Vendors Interface	Incorrect data, Engineering designs not applicable for use
Engineering Site Interface	Engineering personnel are not present on site for the field engineering
Project Completion and Commissioning	Complicated completion due to security concerns, Problems with residents.
Procurement and Logistics Interface	Lack of accurate logistic studies, ineffective logistics routes, permits & licenses required, and customs clearance setbacks.
Logistics and Construction Site	Big shipments, Lack of acceptable packing, bad weather or Political conditions, extended storage time
Major Contractor Subcontractors	Wrong and defective deliveries, Large shipments, Long storage period, Interfaces with several subcontractors and suppliers, Poor training of the contractor's suppliers
Suppliers and Subcontractors/Site Interface	Wrong and defective deliveries, Extended storage time, Contract planning, less productivity of many subcontractors, Poor training of personnel
Commissioning and Operation Interface	Unresolved quality and technical problems, Delayed operational time due to late completion

Enabling Industry 4.0 technologies in SCM involves the application of the Internet of Things (IoT), advanced robotics, and big data analytics. A digital supply chain is interconnected, allowing for interaction, analysis, and information collection to drive significant actions, fundamentally changing how supply chains are managed and operated (Hofman et al., 2019; Goelet et al., 2020). However, research on the role of Big Data in SCM remains limited (Holmström and Partanen, 2014). The term "Big Data" was first introduced at Hannover Messe in 2011 to promote the digitalisation of manufacturing. This paper avails understanding of Big Data technologies and their impacts on SCM. Big Data integrates physical assets and digital technologies through cyber-physical systems (CPS) and IoT (Ghadge et al., 2020). This integration automates and streamlines supply processes, enabling rapid changes in manufacturing and other sectors. Automated systems in Big Data optimise manufacturing speed, customisation, and service operations by consolidating data from various devices (Deloitte, 2014; Luthra and Mangla, 2018). The collaboration of digital technologies transforms traditional supply chains into intelligent systems, offering benefits such as real-time data analysis and increased visibility (Ghadge et al., 2020). Figure 1 below illustrates the key web technologies of Industry 4.0.



Figure 1. Big Data analytics in the Web of Industry 4.0 deployable for SCM

SCM in the era of Big Data is known as SCM 4.0. This approach emphasises the autonomous and digital interconnection between and within companies, requiring organisations to rethink their SCM and design (Frederico et al., 2019; Samahet et al., 2022). SCM 4.0 enhances processes such as reverse logistics, distribution, and planning through Big Data technologies (Michael and Emine, 2019). The growing emphasis on responsibility and sustainability is increasing pressure on companies and their supply chains. Factors such as shifts in customer expectations and new government regulations present new challenges for implementing and managing these chains. Tronnebati and Jawab (2020) explore the distinctions and commonalities between Green Supply Chain Management (GSCM) and SSCM. Their findings indicate that GSCM focuses primarily on environmental, flow, and stakeholder aspects, while SSCM expands this scope to include economic and social dimensions, positioning SSCM as an evolution of GSCM. They advocate for further research into sustainable development in SCM. Samahet al. (2022) also analyse various definitions and practices of SSCM, suggesting that most research has concentrated on "economic" and "environmental" dimensions. They urge for a more vigorous engagement with the social aspect of SSCM and highlight a significant gap in understanding how SSCM affects sustainable performance (Soni and Yadav, 2022; Hsu et al., 2022). Soni and Yadav (2022) examine global trends, challenges, and limitations in SSCM, emphasising the importance of SSCM implementation for businesses to grasp the social, environmental, and economic impacts on their stakeholders. To effectively implement and manage SSCM, digital technologies like visualisation techniques and Artificial Intelligence (AI) are gaining recognition because of their Capability to fulfil economic and societal objectives (Schoormann et al. 2023). Data integration helps managers make informed decisions, monitor performance, and track materials in real time (Lasi et al., 2014). Figure 2 provides a visual representation of the Big Data-enabling technologies that have been impactful across various domains of digitalisation and sustainability.

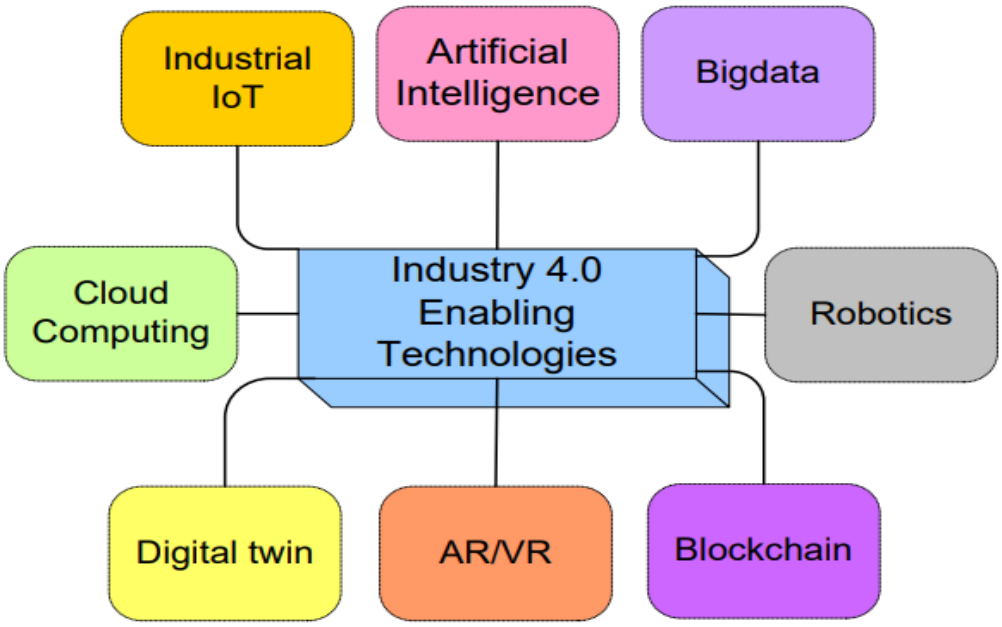

Figure 2. Applicable Industry 4.0 Technologies

SCM is increasingly complex and can benefit significantly from digital transformation. Research shows that a digital, interconnected supply chain can boost speed, agility, and efficiency while reducing operational costs by over 30%, missed sales by more than 60%, and inventory needs by over 70%. SCM also contributes significantly to environmental impact, emitting 33 billion tons of CO2 annually (Mandičák et al., 2021; Ngo et al., 2020). According to McKinsey, supply chains in the consumer-packaged goods sector account for over 80% of greenhouse gas emissions and more than 90% of negative impacts on natural resources (McKinsey, 2022). The UN Sustainable Development Goals (SDGs) apply to various SCM components, including suppliers (SDG 6), logistics (SDG 11), operations (SDG 8), product use (SDG 12), and end-of-life (SDG 13). Big Data plays a crucial role in achieving these goals by enabling better monitoring and analysis of SCM activities (Schoormann et al., 2023). Transitioning to a fully automated and digital supply chain can lead to

operational excellence and significant cost savings (Ghadge et al., 2020). Future industries will integrate connectivity between machines and people within Cyber-Physical Systems (CPS), focusing on developing intelligent products and processes to adapt to rapid changes in consumer behaviour (Brettel et al., 2014). This chapter identifies key Big Data technologies essential to the supply chain sector. Big Data is reshaping how businesses, particularly supply chain companies, manufacture, improve, and distribute products. Technologies such as the Internet of Things (IoT), cloud computing, artificial intelligence (AI), and machine learning are increasingly being integrated into supply chain operations (Frederico et al., 2019; McKinsey and Company, 2022). Understanding these technologies is vital for recommending strategies to companies planning to adopt Big Data.

Big data, defined by Gartner (2012) as "high-volume, high-velocity, and/or high-variety information assets," requires innovative processing forms for better decision-making and process automation. It enables SCM to collect vast amounts of data through sensors, RFID, and tracking devices, enhancing visibility and reducing risks of disruptions (Blanchard, 2014). Mobile computing and data proliferation have created opportunities for process improvements and better demand monitoring (Toole et al., 2015). Implementing big data technologies can lead to operational excellence, cost savings, and improved customer satisfaction, making it an emerging norm in the sector (Raman et al., 2018). Additionally, big data can significantly impact sustainable building design and economic sustainability by lowering costs and reducing material distribution time (Mandicˇák et al., 2021). It also fosters enhancing supply chain and customer relationship management (Anshari et al., 2019). As Ngo et al. (2020) indicate, big data has substantial Capability in engineering, construction, and architecture, supporting supply chain optimisation through effective data analysis.

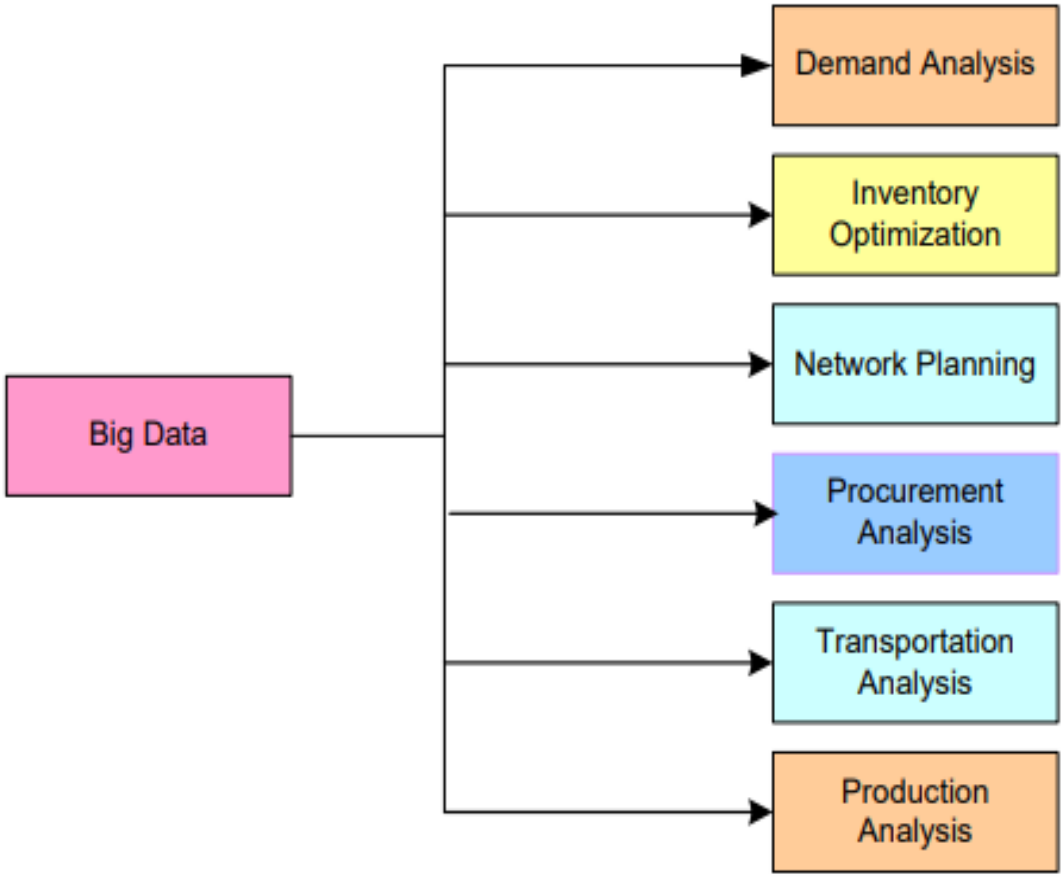

Figure 3. Application of Big Data in sustainable SCM

Table 2. Big data for sustainable SCM

Ref	Objective	Supply Chain	Findings
Dubey, R. et al. (2019).	Examined the impact of building big data analytics for an organisation to enhance supply chain agility.	Supply chain agility.	There is no evidence to support the mediational influence of organisational versatility on the channel of big data analytics capability.
Hsu, C.-H. et al. (2022).	A decision framework that integrates a two-stage House of Quality and multicriteria decision-making was constructed.	Supply chain resilience and mitigation of sustainable supply chain risks.	Management decision-makers can determine where big data analysis enablers can be most cost-effectively improved to promote risk resilience of sustainable supply chains; this ensures the efficient implementation of effective big data strategies.
Al-Khatib, A.W. (2022).	The study assessed the mediating effect of green innovation and the moderating effect of technological intensity.	Green supply chain performance.	It was confirmed that technological intensity moderated the relationship between green innovation and green supply chain performance.
Zhan, Y. and Tan, K.H. (2020).	Integrated infrastructure is needed to break down information silos to improve supply chain performance.	Firms and managers.	Integrating information silos in big data analytics as inputs for novel product concepts.
Brinch, M. (2018).	Reduced the inadequately recognised essence of big data in terms of its significance in SCM from a business process standpoint.	Business processes and decision-making practices.	Value creation, value discovery, and value capture all resemble distinct quality dimensions and offer a multi-faceted standpoint regarding how to realise the value of big data.

SSCM in construction faces numerous challenges and barriers, which are summarised in Table 3 below:

Table 3. Challenges and barriers of SSCM in construction

Reference	Social Challenges
Liu et al. (2018)	The building industry, which uses a lot of energy and emits a lot of pollutants, is under social and environmental pressure as a result of sustainable development
Nantee and Sureeyatanapas. (2021)	Depending on each company's solutions and objectives, the outcome of several warehouse criteria in the construction industry may deteriorate (e.g., increasing electricity bills, maintenance costs and job losses)
Pande and Adil. (2022)	Manufacturing in construction: examines the existing sustainability assessment methodologies for manufacturing enterprises, concluding that the majority of sustainability approaches are difficult to implement due to high skill, data, and time requirements
Fracarolli Nunes and Lee Park. (2017)	While some businesses do strive to meet stakeholders' expectations for sustainable operations, others appear to limit sustainability to public communication
Popović et al. (2017)	Gaps in social sustainability are created by a lack of knowledge, with some of them also being linked to issues in assessing the social sustainability of construction supply chains, which are frequently caused by a lack of adequate quantitative indicators to employ

Table 3 (Cont.). Challenges and barriers of SSCM in construction

Reference	Economic challenges
Martins et al. (2021)	To compete in the face of globalisation, logistics systems must improve process efficiency. For construction and logistics organisations, competitiveness is not only about economics; the idea of the Triple Bottom Line must also be considered
Araújo et al. (2020)	According to the International Organisation for Standardization (ISO), the construction industry is one of the major sectors, and while it generates value and jobs, it also consumes a significant amount of resources, resulting in social and environmental consequences. Conciliating the need for rapid economic expansion with the need for long-term
Bastas and Liyanage. (2018)	Construction firms and supply chains face the multi-faceted problems of not only integrating economic, environmental, and social agendas into their management systems, but also driving continuous sustainability performance improvement.
Hossain et al. (2020).	shortage of circular economy enterprises in the construction sector
	Environmental Challenges
Toufani et al. (2018)	The building industry's growth will result in a significant carbon footprint, both direct and indirect, as well as globalisation and urbanisation, which may result in the loss of green places
Tseng et al. (2021)	Construction and demolition trash continues to wreak havoc on the environment and society. These tough obstacles result in long-term issues that are becoming increasingly critical around the world. Prior research has failed to connect the triple bottom line to a valid estimation or empirical model for estimating construction waste production performance, and there has been no empirical sensitivity analysis in profit maximization
Bartolini et al. (2019)	The increased desire for mass customisation and the expansion of the e-commerce sector have resulted in an increase in the demand for warehouse space and buildings used for construction material storage. Warehouses play a significant role in increasing greenhouse gas emissions in supply chains
Aghelie. (2020)	Because of decreasing energy and natural resources, severe global environmental deterioration, and rising observer comments on personnel health and operational safety, the steelmaking industries are experiencing a great concern about sustainability management

3. Research Methodology

This study explores the capabilities of Big Data Analytics deployment in SSCM for the construction industry, with a focus on identifying relevant technologies, challenges, and potentials of sustainable practices. The study employs a quantitative research design, using a structured questionnaire to elicit data from 485 professionals with over 10 years of experience in the construction industry. By utilising purposive sampling, this study sampled participants who possess extensive knowledge and expertise in the field, thereby ensuring the reliability and validity of the findings. The data collection instrument is a structured questionnaire designed to gather information on various aspects of Big Data deployment to SSCM, including its Capabilities, challenges, and impact. The questionnaire is administered to the selected participants, and the collected data is analysed using statistical software SPSS. The data analysis methods include principal component analysis (PCA), frequency distribution, and percentage, which enable the study to identify patterns and trends in the data. The study's findings are expected to provide valuable insights into the impact of Big Data deployment on SSCM in the construction industry, including the benefits, challenges, and Capabilities of sustainable practices. The results of the study will contribute to the existing literature on SSCM and provide valuable insights for construction industry professionals, policymakers, and researchers who are interested in SSCM. The study's results will be useful for developing strategies to improve the sustainability of supply chain practices in the construction industry.

The research study is divided into several sections, including introduction, literature review, research methodology, data collection, and data analysis. The study uses a comprehensive literature review to identify the research gap and develop a framework for the study. The research design is quantitative, and the data collection instrument is a structured questionnaire. The study uses statistical software SPSS to analyse the data,

and the results are presented using tables and charts. The study's expected outcomes include providing insights into the current state and effectiveness of sustainable supply chain practices in the construction sector. The study aims to contribute to the existing literature on SSCM and provide valuable insights for construction industry professionals, policymakers, and researchers. The study's results will be useful for developing strategies to improve the sustainability of supply chain practices in the construction industry. This research study provides a comprehensive overview of the impact of SSCM in the construction industry. The study's findings will contribute to the existing literature on SSCM and provide valuable insights for construction industry professionals, policymakers, and researchers. The study's results will be useful for developing strategies to improve the sustainability of supply chain practices in the construction industry.

4. Data Analysis

The tables below show the questionnaire distribution of the respondents on exploring the impact of digital technologies on SSCM in South East Nigeria construction projects. A total number of 485 structured questionnaires were administered, and 314 were returned, accepted and used as the basis for the analysis.

Table 4. Response rate *(**Source:** Field Survey, 2025)*

Primary Sources	Total Number	Percentage Total %
Questionnaires distributed	485	100%
Questionnaires returned	314	64.71%
Questionnaires not returned	171	35.29%

The table above shows the number of questionnaires distributed, which was 485; the number of questionnaires returned, which was 314, with a percentage of 64.71%; and the number of questionnaires not returned, which was 30, with a percentage of 35.29%.

Table 5. Frequency Distribution of the Sociodemographic Characteristics of the Respondents *(**Source:** Field Survey 2025)*

Profession		
Architect	46	15%
Builder	68	22%
Civil Structural engineer	80	25%
Mechanical engineering	11	4%
Polymer and Textile Engineer	6	2%
Quantity surveyor	80	25%
Surveying and geoinformatics	23	7%
Total	314	100%
Category of organisation		
Consulting firm	74	24%
Contracting firm	80	25%
Corporate organization	40	13%
Government agency	80	25%
Self employed	40	13%
Total	314	100%

Table 5 (Cont.). Frequency Distribution of the Sociodemographic Characteristics of the Respondents *(**Source:** Field Survey 2025)*

Management Level		
Executive-level management	51	16%
Lower-level management	40	13%
Middle-level management	114	36%
Senior-level management	108	35%
Grand Total	314	100%
Sector		
Residential Buildings	182	58%
Cadastral surveying	17	5%
Engineering firm	29	9%
Heavy/Civil Eng	85	27%
Grand Total	314	100%
Have you used any of the Big Data technologies?		
Yes	314	100%
If yes, which of these Big Data technologies do you use in your organisation?		
Apache Hive	17	5%
Apache Pig	57	18%
Apache Flume	74	24%
Apache Sqoop	29	9%
Google Cloud Data Flow	11	4%
Cloud Computing	11	4%
Stream Processing	6	2%
Data Warehousing	80	25%
Hadoop	23	7%
Apache Spark	6	2%
Grand Total	314	100%

The frequency distribution of the sociodemographic characteristics of the respondents in Table 4.2 provides valuable insight into the reliability of the responses collected in this study on the impact of SSCM in South East Nigeria construction projects. The dataset consists of 55 respondents, with a majority being male (76%) and a smaller proportion being female (24%). This gender distribution may reflect the male-dominated nature of the construction industry in the region. The age distribution of respondents is fairly diverse, with the highest proportion (44%) falling within the 40-50 age range, followed by 31-40 years (31%) and 20-30 years (22%). However, an inconsistency is noted in the 40-30 age category, which may indicate a typographical error. The wide range of age groups represented suggests that the responses capture perspectives from professionals at different career stages. Regarding profession, the sample includes a mix of industry experts, with civil/structural engineers (25%), quantity surveyors (25%), and builders (22%) making up the majority. The presence of other professionals, such as architects, mechanical engineers, and polymer and textile engineers, suggests a multidisciplinary representation, though some professions are underrepresented. In terms of work experience, the majority of respondents (44%) have 16-20 years of professional experience, followed by 6-10 years (31%) and 5 years or less (22%). The predominance of experienced professionals suggests that the data is likely reliable, as it is drawn from individuals with substantial industry knowledge. However, a minor inconsistency is observed in the order of years listed.

Sector-wise, a significant portion of respondents (58%) work in residential buildings, followed by heavy/civil engineering (27%) and an engineering firm (9%). The dominance of residential buildings may

indicate that responses are skewed towards professionals in building structures rather than broader construction supply chain aspects. The geographic distribution of respondents indicates that they work in either Ebonyi (46 respondents) or Enugu (9 respondents). A noteworthy finding is that all respondents (100%) have used Big Data technologies. However, the specific technologies reported vary widely, with Internet of Things (25%), cloud computing (24%), and big data analytics (18%) being the most frequently used. There are inconsistencies in the reporting of Cyber-Physical Systems (CPS) and Internet of Things (IoT), where multiple variations of these terms appear. This inconsistency suggests Capability data entry errors or a lack of clarity in responses. Overall, the frequency distribution suggests that the study includes a diverse range of experienced professionals with relevant expertise. However, minor inconsistencies in some categories and the limited representation of certain professional fields may introduce slight biases.

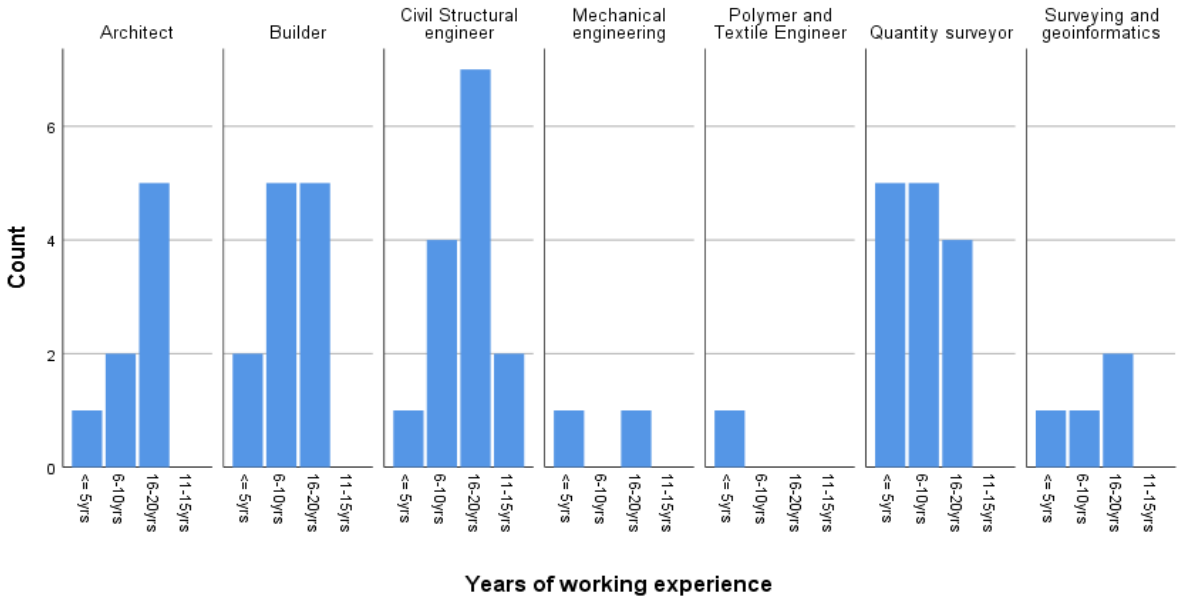

Figure 4. Nested Bar Chart of Years of Working Experience and Profession of the Respondents



Figure 5. Nested Bar Chart of Years of Working Experience and Category of Organisation of the Respondents



Figure 6. Nested Bar Chart of Years of Working Experience and Gender of the Respondents

Table 6. Cronbach's Alpha Reliability Results of the Responses (***Source:*** *Field Survey, 2024*)

S/N	Objective	Cronbach Alpha	No. of Items
1	Capabilities of Big Data Technologies in Sustainable Supply Chain Management		
	Social Capabilities	0.349	4
	Environmental Capabilities	0.761	4
	Economic Capabilities	0.753	4
2	Effective Big Data Technologies used in Sustainable Supply Chain Management	0.747	8
3	Challenges in adopting Big Data Technologies in Sustainable Supply Chain Management		
	Social challenges	0.565	5
	Economic challenges	0.556	4
	Environmental challenges	0.643	4
4	Impact of Big Data Technologies on Sustainable Supply		
	Chain Management in the Construction Industry	0.868	11
	Overall	0.094	44

Table 7. Factor Analysis Sampling Adequacy Analysis Results for the Adequacy of Responses for Factor Analysis (***Source:*** *Field Survey, 2024*)

			Bartlett's Test of Sphericity		
S/N	**Objective**	**Kaiser-Meyer-Olkin Measure of Sampling Adequacy**	**Approx. Chi-Square**	**df**	**Sig.**
1	Capabilities of Big Data Technologies in Sustainable Supply Chain Management				
	Social Capabilities	0.521421085	14.27749034	6	0.026685
	Environmental Capabilities	0.725826971	53.42925207	6	9.61E-10
	Economic Capabilities	0.703303224	59.32810673	6	6.16E-11
2	Effective Big Data Technologies used in Sustainable Supply Chain Management	0.703396364	93.34377739	28	5.91E-09
3	Challenges in adopting Big Data Technologies in Sustainable Supply Chain Management				
	Social challenges	0.504024412	9.802507963	10	0.457988
	Economic challenges	0.63774317	17.09621999	6	0.008936
	Environmental challenges	0.626347406	29.11923356	6	5.78E-05
4	Impact of Big Data Technologies on Sustainable Supply Chain Management in the Construction Industry	0.825443117	220.0851557	55	1.29E-21

Table 6 presents the Cronbach's Alpha reliability results for the responses in the study on "Exploring the Impact of SSCM in South East Nigeria Construction Project." Cronbach's Alpha is a measure of internal consistency, indicating how well the items in a questionnaire measure the intended constructs. A higher Cronbach's Alpha value (typically above 0.7) suggests strong reliability, while lower values may indicate issues with consistency among the items. For the first objective, which examines the Capabilities of Big Data technologies in SSCM, the reliability varies across different dimensions. The social Capabilities category has a relatively low Cronbach's Alpha of 0.349 for its four items, indicating weak internal consistency. However, the environmental Capabilities (0.761) and economic Capabilities (0.753) demonstrate acceptable reliability, suggesting that the items measuring these aspects are consistent in capturing respondents' perceptions. The second objective, which identifies effective Big Data technologies used in SSCM, has a Cronbach's Alpha of 0.747 for its eight items. This value falls within the acceptable range, indicating a good level of reliability in measuring the effectiveness of these technologies. For the third objective, which explores the challenges in adopting Big Data technologies, the reliability results vary across different challenge categories. The social challenges category has a Cronbach's Alpha of 0.565 for its five items, while economic challenges (0.556) and environmental challenges (0.643) also fall below the commonly accepted threshold of 0.7. These moderate reliability values suggest that while the items capture some level of consistency, they may require refinement to improve measurement reliability. The fourth objective, which assesses the impact of Big Data technologies on SSCM in the construction industry, has a high Cronbach's Alpha of 0.868 for its eleven items. This indicates strong internal consistency and suggests that the items effectively measure the intended construct. However, the overall reliability score for all 44 items is extremely low at 0.094. This suggests that there may be significant inconsistencies across the various items in the questionnaire, possibly due to differences in how respondents interpreted the questions or how the constructs were measured. Such a low overall reliability score indicates the need for further refinement of the questionnaire to ensure better consistency across all measured variables.

Table 7 presents the factor analysis sampling adequacy results for evaluating the suitability of responses for factor analysis. The table includes the Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy and Bartlett's test of sphericity. The KMO statistic assesses whether the sample size is adequate for factor analysis, with values closer to 1 indicating strong adequacy, while values below 0.5 suggest poor suitability. Bartlett's test of sphericity examines whether the correlation matrix is significantly different from an identity matrix, with a significant result ($p < 0.05$) indicating that factor analysis is appropriate. For the first objective, which assesses the Capabilities of Big Data technologies in SSCM, the KMO values vary across different dimensions.

The social Capabilities category has a KMO value of 0.521, indicating moderate adequacy, while environmental (0.726) and economic Capabilities (0.703) exhibit good sampling adequacy. Bartlett's test results show that environmental and economic Capabilities have highly significant chi-square values ($p < 0.001$), confirming that factor analysis is appropriate. However, the social Capabilities category has a chi-square value of 14.28 with a p-value of 0.026, which, though significant, is relatively weaker. The second objective, which identifies effective Big Data technologies in SSCM, has a KMO value of 0.703, indicating good sampling adequacy. Bartlett's test result ($\chi^2 = 93.34$, $p < 0.001$) strongly supports the appropriateness of factor analysis for this objective. For the objective, which examines challenges in adopting Big Data technologies, the results are mixed. The social challenges category has a low KMO value of 0.504, suggesting borderline adequacy, and its Bartlett's test result ($p = 0.458$) is not significant, indicating that factor analysis may not be suitable for this subset. In contrast, economic (KMO = 0.638) and environmental challenges (KMO = 0.626) show moderate adequacy, with Bartlett's test results ($p = 0.009$ and $p < 0.001$, respectively) confirming the appropriateness of factor analysis for these dimensions. The fourth objective, which evaluates the impact of Big Data technologies on SSCM in the construction industry, has the highest KMO value of 0.825, indicating excellent sampling adequacy. Bartlett's test result ($\chi^2 = 220.08$, $p < 0.001$) strongly supports the use of factor analysis for this objective. Overall, the results suggest that factor analysis is appropriate for most categories, particularly for environmental and economic Capabilities, effective technologies, economic and environmental challenges, and the impact of Big Data technologies. However, the low KMO value and non-significant Bartlett's test result for social challenges indicate that factor analysis may not be suitable for that category, and further refinement of the questionnaire items may be necessary.

Table 8. Total Variances Explained by the Extracted Components for Assessing Social Capabilities of Big Data Technologies in SSCM *(Extraction Method: Principal Component Analysis)*

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	1.556	38.895	38.895	1.556	38.895	38.895
2	1.050	26.255	65.149	1.050	26.255	65.149
3	.842	21.061	86.210			
4	.552	13.790	100.000			

Table 8 presents the total variance explained by the extracted components in assessing the social Capabilities of Big Data technologies in SSCM. The analysis was conducted using Principal Component Analysis (PCA), which identifies the key components that account for the most variance in the dataset. The "Initial Eigenvalues" column shows the eigenvalues associated with each component before extraction. The first component has an eigenvalue of 1.556, explaining 38.89% of the total variance. The second component has an eigenvalue of 1.050, contributing an additional 26.26% of the variance. Together, these two components account for a cumulative variance of 65.15%, meaning they explain 65.15% of the total variability in the data. The third and fourth components have eigenvalues below 1 (0.842 and 0.552, respectively) and contribute less variance (21.06% and 13.79%). Since PCA typically retains only components with eigenvalues greater than 1 (based on the Kaiser criterion), only the first two components are extracted, as indicated in the "Extraction Sums of Squared Loadings" column. These extracted components retain the same variance explanation as in the initial eigenvalues, reinforcing that they effectively summarise the dataset. The factor analysis suggests that two key components adequately capture the majority (65.15%) of the variance in the social Capabilities of Big Data technologies, while the remaining components contribute relatively little information. This indicates that the underlying structure of the dataset can be effectively represented using these two components.

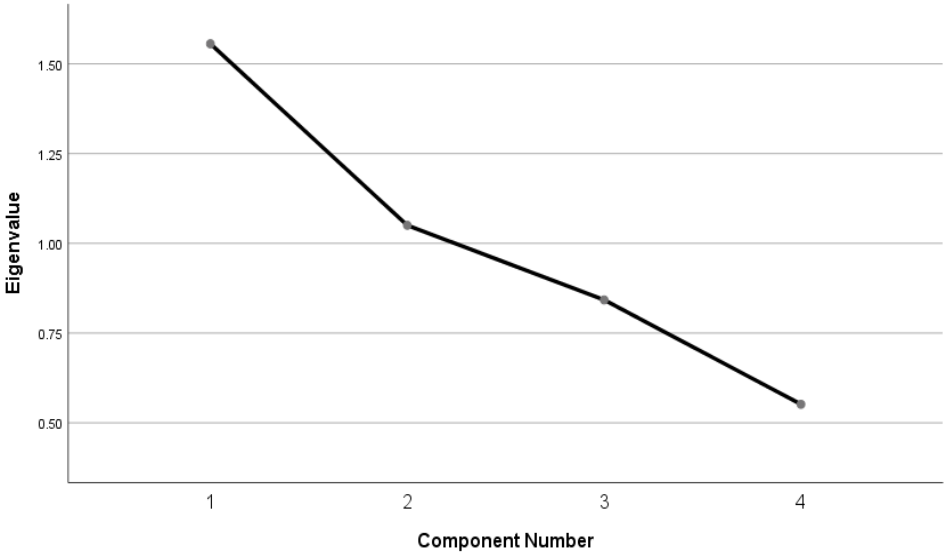

Figure 7. Scree Plot for the Optimal Number of Components for Assessing Social Capabilities of Big Data Technologies in SSCM

The scree plot in Figure 7 visually represents the eigenvalues associated with each principal component for assessing the social Capabilities of Big Data technologies in SSCM. The plot shows a clear decline in eigenvalues as the component number increases, indicating the relative importance of each component. From the graph, the first two components have eigenvalues greater than 1, which aligns with the results in Table 4.5. This suggests that these two components account for the majority of the variance in the dataset and should be retained for further analysis. The third and fourth components have eigenvalues below 1 and contribute less variance, supporting their exclusion based on the Kaiser criterion. The "elbow" in the scree plot, where the eigenvalues begin to level off, occurs at the second component. This confirms that a two-component solution is optimal for summarising the key patterns in the data.

Table 9. Component Matrix of the Factor Loadings for Assessing Social Capabilities of Big Data Technologies in SSCM *(Extraction Method: Principal Component Analysis)*

	Component	
	1	**2**
The implementation of Big Data Technologies	.809	-.205
The transition of logistics transportation systems	.686	.323
smart warehouse management and smart production system	.640	-.289
New companies are to rely solely on their own strengths	.143	.906

The component matrix in Table 9 presents the factor loadings, which indicate the correlation between each variable and the extracted components. Higher absolute values of loadings suggest a stronger association between the variable and the corresponding component. In this case, two components were extracted. The first component has strong positive loadings for "The implementation of Big Data Technologies" (0.809), "The transition of logistics transportation systems" (0.686), and "Smart warehouse management and smart production system" (0.640). This suggests that these variables are closely related and collectively define the first component. The second component has a strong loading for "New companies to rely solely on their own strengths" (0.906), meaning this variable is distinct and primarily associated with the second component. Among these variables, "The implementation of Big Data Technologies" has the highest loading (0.809) on the first component, making it the most significant social Capability factor in Big Data adoption for SSCM. This suggests that implementing these technologies plays a crucial role in transforming social aspects of supply chain sustainability, likely through improved efficiency, communication, and collaboration across stakeholders.

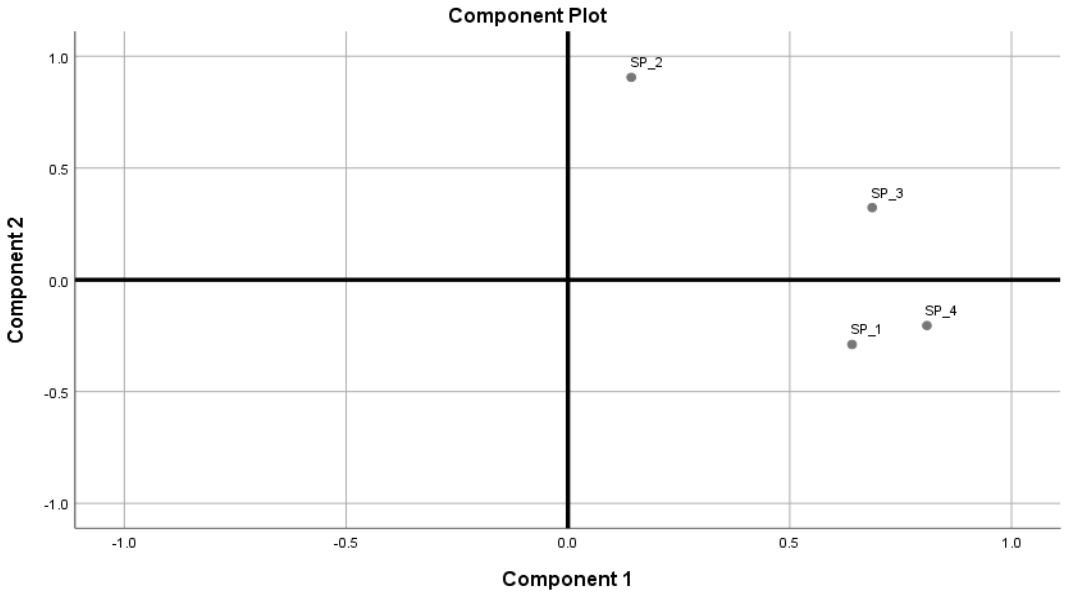

Figure 8. Components Plot of the Extracted Components for Assessing Social Capabilities of Big Data Technologies in SSCM

The component plot visually represents how the four assessed social Capability factors of Big Data technologies are distributed across the two extracted components. The factor distribution across components shows that "The implementation of Big Data Technologies" and "The transition of logistics transportation systems" are closely positioned on Component 1, suggesting they are strongly related and primarily explained by this component. "Smart warehouse management and smart production system" also has a notable contribution to Component 1, but is slightly distinct. In contrast, “New companies to rely solely on their own strengths” are more associated with Component 2, indicating it has different underlying characteristics compared to the other three factors. Component 1 appears to explain most of the variance for three out of the four factors, meaning it captures the primary dimension of social Capabilities in Big Data adoption. Component 2 mainly explains "The transition of logistics transportation systems," indicating a separate influence or dimension in social Capability. Based on the factor loadings in Table 4.5, "The implementation of Big Data Technologies" had the highest loading (0.809) on Component 1. This confirms that "The implementation of Big Data Technologies" is the most significant social Capability factor in SSCM. The findings suggest that the implementation of Big Data technologies plays the most crucial role in enhancing social aspects of sustainable supply chains, while logistics transition represents a different, yet relevant, dimension. The results emphasise the need for organisations to focus on digital transformation strategies, automation, and smart production to achieve social sustainability in SCM.

Table 10. Total Variances Explained by the Extracted Components for Assessing Environmental Capabilities of Big Data Technologies in SSCM *(Extraction Method: Principal Component Analysis)*

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	2.334	58.344	58.344	2.334	58.344	58.344
2	.716	17.888	76.232			
3	.586	14.661	90.893			
4	.364	9.107	100.000			

The total variance explained by the extracted components for assessing the environmental Capabilities of Big Data technologies in SSCM indicates that only one principal component was retained. The first component has an eigenvalue of 2.334 and explains 58.344% of the total variance, suggesting that it captures the most

significant environmental Capability factor. The second, third, and fourth components have eigenvalues below 1, with cumulative variances of 76.232%, 90.893%, and 100%, respectively. However, since only the first component has an eigenvalue greater than 1, it is the most meaningful factor in explaining environmental Capabilities. The results imply that a single dominant factor largely accounts for the environmental impact of Big Data technologies in sustainable supply chains. This suggests that environmental benefits, such as energy efficiency, waste reduction, and resource optimisation, may be driven by a common underlying factor rather than multiple independent dimensions.

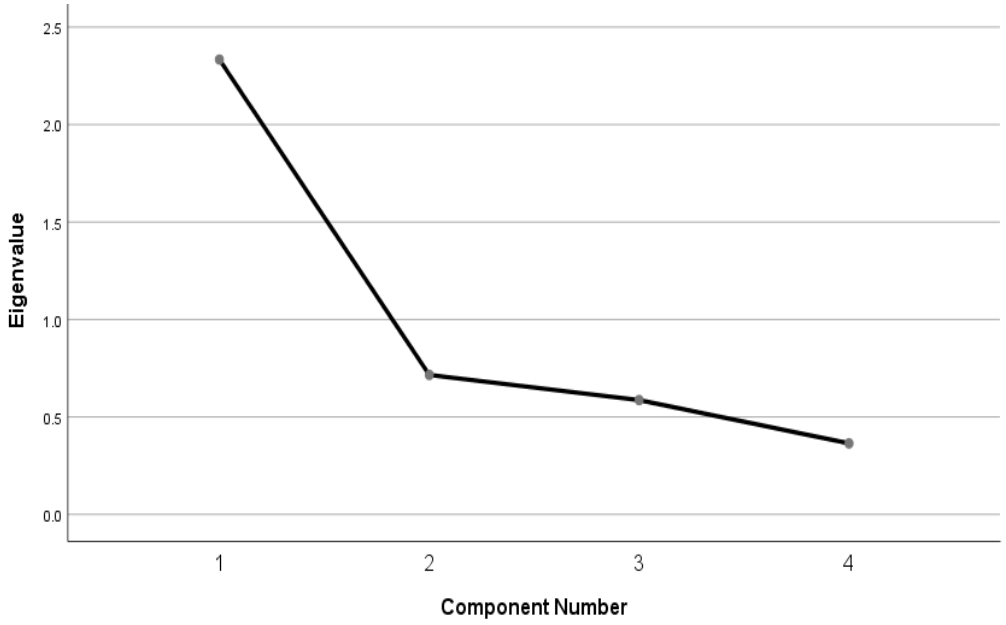

Figure 9. Scree Plot for the Optimal Number of Components for Assessing Environmental Capabilities of Big Data Technologies in SSCM

Table 11. Component Matrix of the Factor Loadings for Assessing Environmental Capabilities of Big Data Technologies in SSCM *(Extraction Method: Principal Component Analysis)*

	Component
	1
Environmental sustainability enablers for the steel Industry	.842
To use top-ranked sustainability indicators	.770
To improve pollution emission control capabilities	.754
Energy conservation and emission reduction Technologies	.681

Table 11 presents the component matrix of factor loadings derived from a Principal Component Analysis (PCA) conducted to assess the environmental Capabilities of Big Data technologies in SSCM. PCA is a statistical method used to reduce the dimensionality of data, identifying underlying factors that explain the most variation in the dataset. In this case, the table outlines the environmental sustainability enablers and their loadings on the identified component, which likely represents a factor related to environmental sustainability in the steel industry within the context of Big Data technologies. The highest factor loading, 0.842, corresponds to "Environmental sustainability enablers for the steel industry." This suggests that the role of enablers, such as policies, regulations, and organisational strategies, is the most significant driver of improving environmental sustainability in the steel industry. These enablers are foundational to achieving sustainability goals and adopting Big Data technologies. Another significant factor, with a loading of 0.770, is the importance of using top-ranked sustainability indicators. This factor emphasises the need for clear and reliable metrics to monitor and assess environmental performance, which is crucial for guiding sustainability efforts in SCM. The factor

with a loading of 0.754 represents the need to improve pollution emission control capabilities. This suggests that Big Data technologies can significantly enhance emission control systems, reducing the environmental impact of industrial processes.

The factor "Energy conservation and emission reduction technologies" has a loading of 0.681, highlighting the significance of technologies that focus on energy efficiency and emission reduction. Big Data technologies, such as automation and data analytics, can optimise energy usage and minimise emissions, contributing to sustainability efforts. The most significant environmental Capability, based on the component matrix, appears to be "Environmental sustainability enablers for the steel industry" with a factor loading of 0.842. This factor is critical because it underscores the importance of having a strong foundation of enablers, such as policies and organisational commitment, to effectively implement sustainability initiatives. Without these enablers, the adoption of technologies aimed at pollution control, energy conservation, and emission reduction would be less effective. Therefore, enablers play a vital role in ensuring the success of Big Data technologies in achieving long-term sustainability goals in the steel industry.

Table 12. Total Variances Explained by the Extracted Components for Assessing Economic Capabilities of Big Data Technologies in SSCM *(Extraction Method: Principal Component Analysis)*

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	2.309	57.733	57.733	2.309	57.733	57.733
2	.862	21.544	79.277			
3	.523	13.078	92.355			
4	.306	7.645	100.000			

Table 12 presents the total variances explained by the extracted components for assessing the economic Capabilities of Big Data technologies in SSCM. The table is based on Principal Component Analysis (PCA), which identifies the key components that explain the variation in the data. The first component has an initial eigenvalue of 2.309, which explains 57.733% of the total variance. This component accounts for the majority of the variation in the dataset, indicating that it captures the most significant underlying economic factors related to Big Data technologies in the supply chain. After extraction, this component still explains 57.733% of the variance, confirming its dominance in the model. The second component has an eigenvalue of 0.862, explaining 21.544% of the variance. This brings the cumulative variance explained by the first two components to 79.277%, indicating that these two components together account for a substantial portion of the variation in the data. The third component, with an eigenvalue of 0.523, explains 13.078% of the variance. Adding this to the cumulative total brings the variance explained by the first three components to 92.355%. The fourth component has a smaller eigenvalue of 0.306, which accounts for 7.645% of the variance. This completes the cumulative total of 100% of the variance explained by all four components. Overall, the first component is the most significant, explaining more than half of the variance, while the remaining components contribute to the cumulative variance, but to a lesser extent. The extraction method used is Principal Component Analysis, which helps to identify the key components that explain the economic Capabilities of Big Data technologies in the context of SSCM.

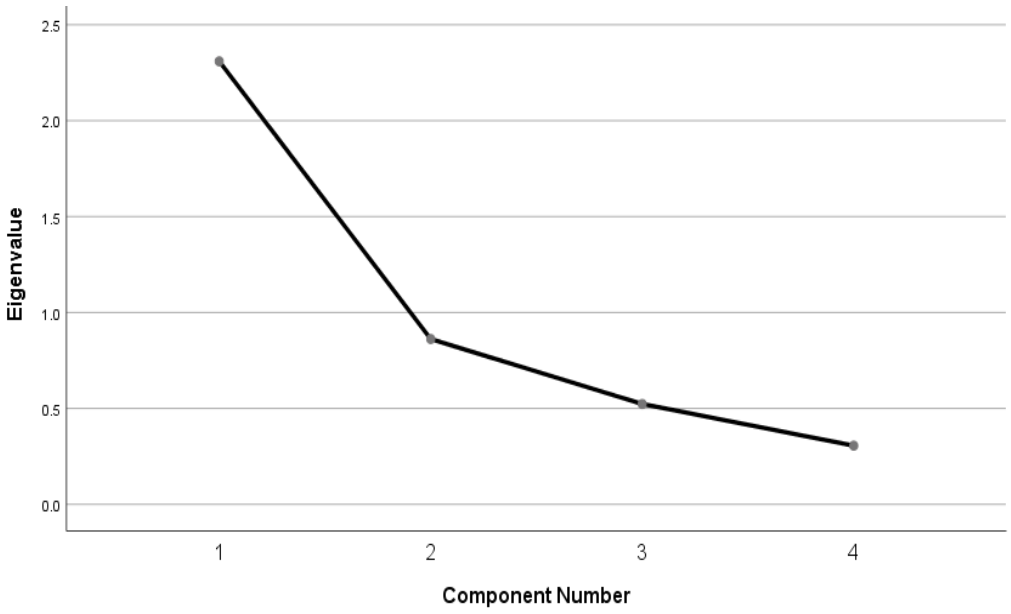

Figure 10. Scree Plot for the Optimal Number of Components for Assessing Economic Capabilities of Big Data Technologies in SSCM

Table 13. Component Matrix of the Factor Loadings for Assessing Economic Capabilities of Big Data Technologies in SSCM *(Extraction Method: Principal Component Analysis)*

	Component
	1
To improve economic growth & environmental preservation	.867
Increase Sustainable manufacturing and the circular economy	.827
Increase efficiency of materials, information, and cash flow	.799
To address the economic concerns of emerging countries	.486

Table 13 presents the component matrix of factor loadings for assessing the economic Capabilities of Big Data technologies in SSCM. The table highlights the factor loadings of different variables that contribute to the first identified component, derived from Principal Component Analysis (PCA). The factor with the highest loading of 0.867 is "To improve economic growth & environmental preservation." This suggests that the adoption of Big Data technologies has a strong Capability to contribute to both economic growth and environmental preservation, making it a key focus for achieving sustainable development goals. The second factor, "Increase sustainable manufacturing and circular economy," has a loading of 0.827, indicating that Big Data technologies can play a significant role in promoting sustainable manufacturing practices and supporting the transition to a circular economy. This is crucial for reducing waste and improving resource efficiency in supply chains. The third factor, "Increase efficiency of materials, information, and cash flow," with a loading of 0.799, emphasises the Capability of Big Data technologies to enhance operational efficiency. By improving the management of materials, information, and cash flow, these technologies can drive cost savings and better resource utilisation, contributing to economic sustainability. The fourth factor, "To address the economic concerns of emerging countries," has a loading of 0.486, which is relatively lower than the others. This indicates that while Big Data technologies may address economic concerns in emerging countries, it is a less significant factor compared to the other variables in driving economic Capability. Overall, the first component, based on the factor loadings, indicates that the most significant economic Capability of Big Data technologies lies in improving economic growth and environmental preservation, promoting sustainable manufacturing, and increasing efficiency in the supply chain. The factor addressing economic concerns in emerging countries, while relevant, appears to be of lesser importance in the context of the analysed economic Capabilities.

5. Conclusion

The study's findings reveal that Big Data technologies have significant social, environmental, and economic Capabilities in the context of SSCM. Specifically, the implementation of Big Data technologies emerges as the most significant social Capability factor, with a loading of 0.809 on the first component. This suggests that these technologies play a crucial role in transforming social aspects of supply chain sustainability, likely through improved efficiency, communication, and collaboration across stakeholders. In terms of environmental sustainability, Big Data technologies such as energy conservation, pollution emission control, and sustainable practices are key enablers. These technologies contribute to the improvement of sustainability indicators and the reduction of pollution, thereby enhancing the environmental sustainability of the steel industry. From an economic perspective, Big Data technologies drive growth and environmental preservation by increasing manufacturing efficiency, promoting circular economy principles, and addressing economic concerns of emerging countries. These technologies enhance materials, information, and cash flow efficiency, ultimately contributing to the overall sustainability of the supply chain. Overall, the study's findings highlight the critical role that Big Data technologies can play in promoting SSCM. By leveraging these technologies, organisations can improve their social, environmental, and economic performance, ultimately contributing to a more sustainable future. The key findings of the study can be summar8ised as follows: Big Data technologies have significant social Capabilities, including improved efficiency, communication, and collaboration across stakeholders. They also have environmental Capabilities, such as energy conservation, pollution emission control, and sustainable practices. Additionally, Big Data technologies have economic Capabilities, including increased manufacturing efficiency, promotion of circular economy principles, and enhanced materials, information, and cash flow efficiency. These findings have important implications for organisations seeking to adopt SSCM practices. By investing in Big Data technologies, organisations can improve their sustainability performance, reduce their environmental impact, and drive economic growth.

6. Recommendations

Based on the extensive study conducted on the impact of digital technologies on SSCM in construction projects, several key recommendations emerge. Firstly, it is imperative for companies to invest in Big Data technologies, such as the Internet of Things (IoT), Artificial Intelligence (AI), and blockchain, to enhance supply chain sustainability. By leveraging these technologies, companies can improve efficiency, reduce waste, and promote sustainable practices throughout the supply chain. Secondly, organisations should develop a strategic roadmap for the adoption of Big Data technologies, taking into account both the benefits and challenges associated with their implementation. This will enable companies to navigate the complexities of digital transformation and ensure a smooth transition to more sustainable practices. Finally, companies should prioritise collaboration and transparency throughout the supply chain, utilising Big Data technologies to promote sustainable practices and foster a culture of accountability and responsibility. By implementing these recommendations, companies can harness the capabilities of Big Data technologies to drive SSCM and contribute to a more environmentally friendly and socially responsible construction industry.

Author Contributions The research was conceptualised, the proof was provided, and S.E. and M.I prepared the initial draft. The literature was reviewed by N.A., who provided replaceable suggestions and a final draft.

Data Availability and Material Statement No primary data were collected or analysed, but rather synthesised and interpreted findings from previous studies to develop a conceptual model. It relied on existing literature to inform the theoretical framework and analytical approach. All sources are publicly available and cited.

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Declarations

Competing Interests The authors declare no competing interests.

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